HYBRID METAHEURISTIC METHOD FOR CLUSTERING IN WIRELESS SENSOR NETWORKS

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KUALA LUMPUR

2023

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THESIS SUBMITTED IN FULFILMENT OF THE REQUIREMENTS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

FACULTY OF COMPUTER SCIENCE AND INFORMATION TECHNOLOGY
UNIVERSITI MALAYA
KUALA LUMPUR

2023

UNIVERSITI MALAYA

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HYBRID METAHEURISTIC METHOD FOR CLUSTERING IN WIRELESS SENSOR NETWORKS

ABSTRACT

Wireless Sensor Networks (WSNs) are used widely in many applications to ease data access in large-scale and hard-to-reach areas. However, WSNs possess many limitations, such as limited energy, memory size and communication ranges. Energy is the biggest concern in WSNs, as these nodes are deployed randomly in hard-to-reach sensing fields. So, the idea of replacing the battery is not a viable option. To alleviate the problem, clustering techniques were proposed in the early 2000s. However, it faced issues such as isolated node problems and energy hole problems because of the inefficiency in Cluster Head (CH) selection. As such, the existence of metaheuristic methods to optimally select the CH and forms clusters has opened up a research interest in proposing a metaheuristic method with balanced exploration and exploitation ability for efficient CH selection. As such, this thesis proposes a hybrid metaheuristic method that consists of Sperm Swarm Optimization (SSO) algorithm and Genetic Algorithm (GA), which is termed HSSOGA. To ensure the performance of the developed method in obtaining the optimized solution, the method is evaluated on 11 test benchmark functions named Sphere, SumSquare, Zakharov, Rosenbrock, Step, Ackley, Griewank, Rastrigin, Schwefel 2.26, Michalewicz and Egg Crate. The results obtained by the proposed HSSOGA in optimizing this function was promising as it ranked first in the majority of the test function compared to existing hybrid metaheuristic method such as HFPSO, HPSOGA, SAGA, PSOGWO, HSSOGSA and existing conventional methods termed SSO and GA. Then, the proposed HSSOGA is enhanced by adaptively tuning the crossover and mutation probability, as well as linearly reducing the velocity of the sperms to ensure the exploration and exploitation of the method are controlled based on network changes. The adaptive HSSOGA (aHSSOGA) is implemented in the WSN environment to mitigate the isolated node and energy hole problems. To assist the proposed method, the objective functions used to select optimal CH is refined by adding objectives such as CH's maximum neighbour node and average isolated node probability. Moreover, two improvised clustering techniques are introduced to reduce the energy overhead cost from the re-clustering process. The performance of aHSSOGA is evaluated based on average residual energy, network lifetime, total re-clustering occurrence, total data delivery, network throughput and end-to-end delay metrics. The proposed aHSSOGA outperforms the state-of-the-art.

Keywords: Cluster Head Selection, Metaheuristic, Optimization, Wireless Sensor Network.

KAEDAH METAHEURISTIK HIBRID UNTUK PENGELOMPOKAN DALAM RANGKAIAN PENDERIA TANPA WAYAR

ABSTRAK

Rangkaian Penderia Tanpa Wayar (WSN) digunakan secara meluas dalam banyak aplikasi untuk memudahkan capaian data dalam kawasan berskala besar dan sukar dicapai. Walau bagaimanapun, WSN mempunyai banyak batasan, seperti tenaga terhad, saiz memori dan julat komunikasi. Tenaga adalah kebimbangan terbesar dalam WSN, kerana nod ini digunakan secara rawak dalam medan penderiaan yang sukar dicapai. Jadi, idea untuk menggantikan bateri bukanlah pilihan yang berdaya maju. Untuk mengurangkan masalah tersebut, teknik pengelompokan telah dicadangkan pada awal tahun 2000-an. Walau bagaimanapun, ia menghadapi isu seperti masalah nod terpencil dan masalah lubang tenaga kerana ketidakcekapan dalam pemilihan Ketua Kluster (CH). Oleh yang demikian, kewujudan kaedah metaheuristik untuk memilih CH secara optimum dan membentuk kluster telah membuka minat penyelidikan untuk mencadangkan kaedah metaheuristik dengan keupayaan penerokaan dan eksploitasi yang seimbang untuk pemilihan CH yang cekap. Oleh yang demikian, tesis ini mencadangkan kaedah metaheuristik hibrid yang terdiri daripada algoritma Pengoptimuman Swarm Sperma (SSO) dan Algoritma Genetik (GA), yang dinamakan HSSOGA. Untuk memastikan prestasi kaedah yang dibangunkan dalam mendapatkan penyelesaian yang dioptimumkan, kaedah tersebut dinilai pada 11 fungsi penanda aras ujian yang dinamakan Sphere, SumSquare, Zakharov, Rosenbrock, Step, Ackley, Griewank, Rastrigin, Schwefel 2.26, Michalewicz dan Egg Crate. Keputusan yang diperolehi oleh HSSOGA yang dicadangkan dalam mengoptimumkan fungsi ini adalah menjanjikan kerana ia menduduki tempat pertama dalam majoriti fungsi ujian berbanding kaedah metaheuristik hibrid sedia ada seperti HFPSO, HPSOGA, SAGA, PSOGWO, HSSOGSA dan kaedah konvensional sedia ada yang dinamakan SSO dan GA. Kemudian, HSSOGA yang dicadangkan dipertingkatkan dengan menyesuaikan kebarangkalian crossover dan mutasi secara adaptif, serta mengurangkan halaju sperma secara linear untuk memastikan penerokaan dan eksploitasi kaedah dikawal berdasarkan perubahan rangkaian. HSSOGA adaptif (aHSSOGA) dilaksanakan dalam persekitaran WSN untuk mengurangkan masalah nod terpencil dan lubang tenaga. Untuk membantu kaedah yang dicadangkan, fungsi objektif yang digunakan untuk memilih CH optimum diperhalusi dengan menambahkan objektif seperti nod jiran maksimum CH dan kebarangkalian nod terpencil purata. Selain itu, dua teknik pengelompokan terbaharu diperkenalkan untuk mengurangkan kos overhed tenaga daripada proses pengelompokan semula. Prestasi aHSSOGA dinilai berdasarkan purata tenaga sisa, hayat rangkaian, jumlah kejadian pengelompokan semula, jumlah penghantaran data, daya pemprosesan rangkaian dan metrik kelewatan hujung ke hujung. Kaedah aHSSOGA yang dicadangkan mengatasi prestasi terkini.

Kata Kunci: Pemilihan Ketua Kluster, Metaheuristik, Pengoptimuman, Rangkaian Penderia Tanpa Wayar.

ACKNOWLEDGEMENTS

First and foremost, I would like to thank the Almighty God for giving me the knowledge, wisdom and strength throughout the period of my research and thesis writing.

I would like to convey my sincere thankfulness to my supervisors, Associate Professor Ts. Dr. Ismail Ahmedy and Associate Prof. Dr. Mohd Yamani Idna Idris for their constant support and guidance throughout my candidature period. Their inputs and technical ideas have led me in producing valuable research as presented in this thesis. Moreover, the knowledge shared through them has broaden my knowledge in the field of research. I would also like express my gratitude to Professor Ts. Dr. Rafidah Md Noor for her guidance towards publishing two required articles for the completion of my PhD. Her inputs have given me better understanding in writing techniques for research.

Furthermore, I would thank my loved one, Deborah Grace, family and friends who have been giving me mental and moral support throughout my PhD journey. As their moral support kept me working harder to achieve higher without breaking. So, I would like to also dedicate this achievement of PhD to them.

Finally not forgetting the staffs of Faculty of Computer Science and Information Technology, Universiti Malaya and staffs of Human Talent management Division, Universiti Malaya for processing of SLAI scholarship throughout my PhD studies as well as fulfilling the needs that I requested.

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LIST OF SYMBOLS AND ABBREVIATIONS

EED_r	:	end-to-end delay for every round.
E_r	:	average residual energy for each round.
G	:	gravitational constant.
RC	:	re-clustering trigger.
TDD_r	:	total data delivery for every round.
$Throughput_r$	:	Network throughput.
V_i	:	velocity of the sperm.
μ	:	mean.
σ	:	standard deviation.
mu	:	Mutation Rate.
pc	:	Crossover Percentage.
pm	:	Mutation Percentage.
ABC	:	Artificial Bee Colony.
ACO	:	Ant Colony optimization.
aHSSOGA	:	Adaptive Hybrid Sperm Swarm Optimization and Genetic Algorithm.
BS	:	base station.
CCH	:	collecting cluster head.
CH	:	cluster head.
CSMA	:	carrier-sense multiple access.
EE	:	elementary effect matrix.
EW	:	elementary weight matrix.
FND	:	First Node Death.
GA	:	Genetic Algorithm.
GSA	:	Gravitational Search Algorithm.
HFAPSO	:	Hybrid Firefly Algorithm with Particle Swarm Optimization.
HFPSO	:	Hybrid Firefly and Particle Swarm Optimization.
HGWOSFO	:	Hybrid Grey Wolf Optimizer and Sunflower Optimization.
HND	:	Half Node Death.
HPSOGA	:	Hybrid Particle Swarm Optimization and Genetic Algorithm.
HRH	:	High-level Relay Hybrid.
HSAPSO	:	Hybrid Harmony Search Algorithm with Particle Swarm Optimization.
HSSOGA	:	Hybrid Sperm Swarm Optimization and Genetic Algorithm.

HSSOGSA	:	Hybrid Sperm Swarm Optimization and Gravitational Search Algorithm.
HTH	:	High-level Teamwork Hybrid.
ISM	:	Industrial, Scientific and Medical.
LEACH	:	Low-Energy Adaptive Clustering Hierarchy.
LND	:	Last Node Death.
LNP	:	leather nesting problem.
LR-WPAN	:	Long Range Wireless Personal Area Network.
LRH	:	Low-level Relay Hybrid.
LSGO	:	Large Scale Global Optimization.
LTH	:	Low-level Teamwork Hybrid.
MANET	:	Mobile ad-hoc network.
OBS	:	Optical Burst-Switched.
PDR	:	packet delivery ratio.
PSO	:	Particle Swarm Optimization.
PSOGWO	:	hybrid Particle Swarm Optimization and Grey Wolf Optimizer.
R-CND	:	Re-Clustering after a Node Dead.
RO	:	research objectives.
RQ	:	research questions.
SAGA	:	hybrid Simulated Annealing and Genetic Algorithm.
SCH	:	sub-cluster head.
SSO	:	Sperm Swarm optimization.
TDMA	:	time-division multiple access.
V2V	:	vehicle-to-vehicle.
WoS	:	Web of Science.
WSN	:	wireless sensor network.

LIST OF APPENDICES

CHAPTER 1: INTRODUCTION

1.1 Background of Study

In this 21st century era, technology has developed and grown rapidly because of its functionality in making life easier. Many technologies opt to have wireless communications because of their mobility, easier accessibility, and no limitation to the number of connectivity (Khan & Tariq, 2018). The most popular wireless protocols are Bluetooth (IEEE 802.15.1) and Wi-Fi (IEEE 802.11) where Bluetooth is used for smaller technologies that are power-limited and short-range transmissions (10 m) with a communication frequency band of 2.5 GHz, while Wi-Fi is used for more extensive technologies to communicate and for a long-range transmission (100m) with a communication frequency band up to 5 GHz (Ferro & Potorti, 2005). The dominance of these wireless protocols calls for many technological development advances, especially sensor-based infrastructures. It has contributed significantly towards various fields such as environmental monitoring, military, healthcare application and transportation (Singh et al., 2017). A Wireless sensor network (WSN) comprises small sensor nodes limited to communication ranges, memory size, and power in the battery, which can self-configure to form a network. These nodes are said to be capable of sensing, wireless communication, and computation (Matin & Islam, 2012; Singh et al., 2017), where sensed data are transmitted to a base station (BS) for the end-user to analyse and validate the data.

Since WSNs' nature is to operate on a large scale, the Bluetooth protocol seems to be inappropriate to be utilised. So, a protocol was created to cater to long-range (10 - 75m) with lesser power consumption named Long Range Wireless Personal Area Network (LR-WPAN) -IEEE 802.15.4, later called ZigBee technology. ZigBee is almost similar to Bluetooth protocol but simpler as it has lower energy consumption and data rate with a higher operational range compared to Bluetooth.

The creation of ZigBee technologies with their advantages has drawn attention towards greater development and usage of WSNs. Even though ZigBee devices can last up to two years, replacing batteries on large scales can be tedious. So, the expansion of WSN usage with the limitation based on energy has been affecting the optimised usage of WSN in the aforementioned applications. Energy concerns of WSN have become a core point of research where in the early 2000s, Low-Energy Adaptive Clustering Hierarchy (LEACH) protocol was proposed by (W. R. Heinzelman et al., 2000) to overcome the energy efficiency problem. The protocol seems successful as it introduces a clustering approach which groups the nodes into clusters and selects a cluster head (CH) to aggregate and transfer data to BS. The Clustering approach is deemed a great leap compared to traditional WSN deployment as it performs better in all aspects, such as energy, communication, and stability. The concept of traditional WSN and clustered WSN are illustrated in the figure below:

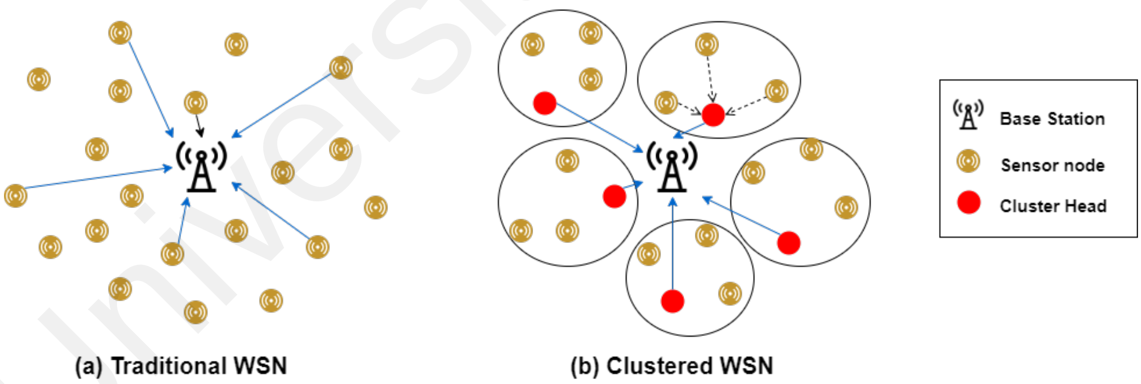

Figure 1.1: Concept of Traditional and Clustered WSN.

In traditional WSN, each node will sense the data and send its data to BS by itself (Vlajic & Xia, 2006). So, the nodes located far away from the BS tend to use more energy as the distance to transmit data is further, causing the nodes at a distance to die off quickly. This issue causes the network to be non-reliable and inefficient for data gathering in crucial applications such as healthcare and disaster monitoring applications. On the other hand, clustering has two core steps which are the CH selection and cluster formation phases. LEACH selects the cluster heads randomly on a rotational basis to balance out the energy distribution of the network. Upon selecting the appropriate CHs, the non-CH nodes will calculate their distance to the nearest CH and join as a member to the CH where clusters are formed. So, the member nodes send the sensed data to the CH, which is nearer compared to BS, where it reduces the energy consumption of the nodes, and prolong the network lifetime (W. R. Heinzelman et al., 2000).

Since LEACH was a great success from the traditional WSN layout, researchers started to explore and study LEACH deeper, and some researchers modified the LEACH approach. The random selection of CHs was not optimal for energy distribution as energy-aware CH selection protocols with the inclusion of additional selection criteria were developed for better performance (Pour & Javidan, 2021). On the other hand, some researchers include metaheuristic approaches to select optimal CH and cluster formation (Cai et al., 2019; Kirsan et al., 2020). This is because metaheuristic methods are deemed to give out quality results in a short period for many optimisation scenarios (D. Prasad et al., 2017). The inclusion of metaheuristic methods in LEACH has shown great advancement as it is easier to deploy and needs less effort in planning for the deployment of WSN. Since then, many metaheuristic methods have been tested in the context of clustering of WSN.

Metaheuristic means a high-level procedure that may provide a sufficiently good solution to an optimisation problem (Bianchi et al., 2009) consisting of nature or bio-inspired algorithms built based on the system's behaviour. Metaheuristic methods are famous for their exploration and exploitation abilities to ensure efficient optimisation (Abdel-Basset et al., 2018). WSNs used on a large scale are categorised as multimodal optimisation functions. Multimodal function has many local optima and one global optimum in a search space (K.-C. Wong, 2015). On the other hand, unimodal functions are simple optimisation problems with only one similar global and local optima. Both examples of multimodal and unimodal test functions from the Virtual Library of Simulation and Experiments (Surjanovic & Bingham, 2013) are depicted in Figure 1.2 and Figure 1.3 for better understanding.

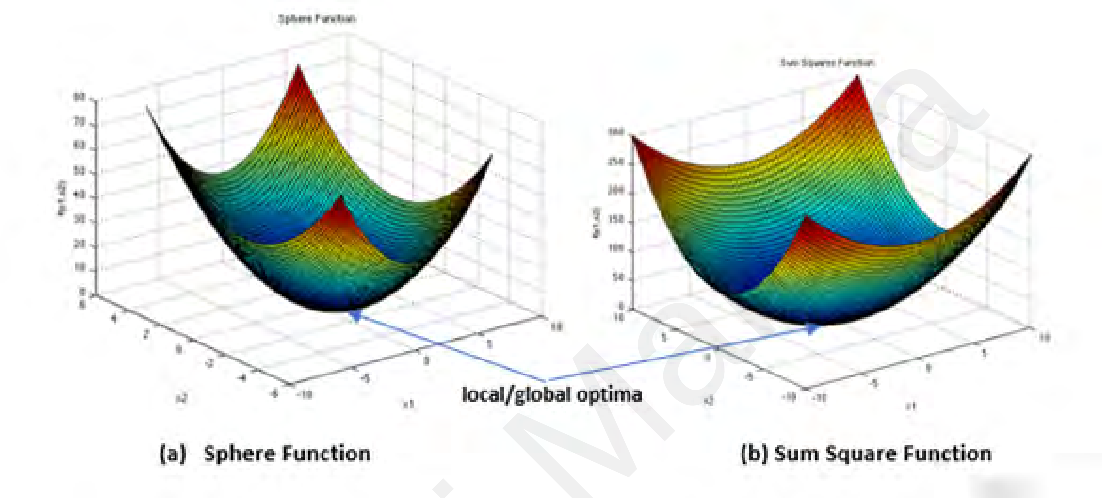

Figure 1.2: Unimodal test Functions.

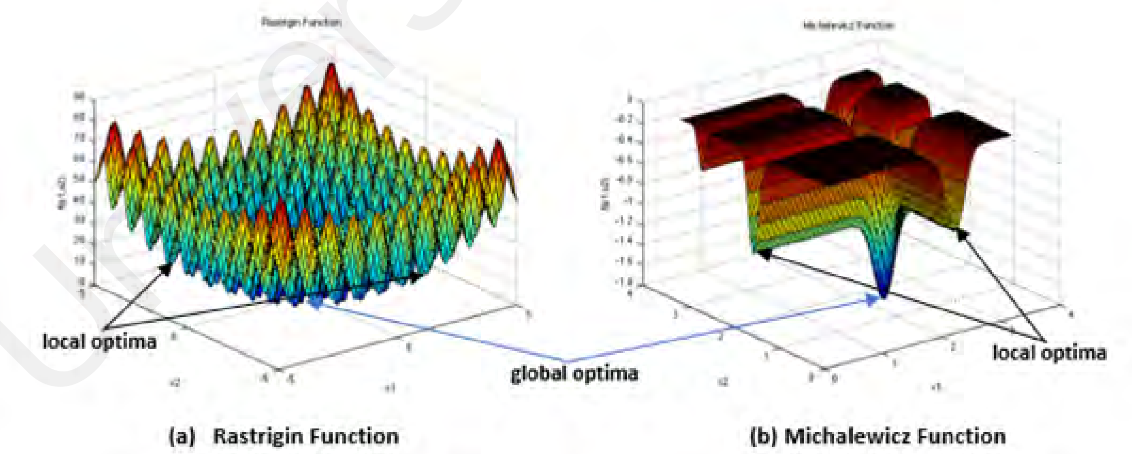

Figure 1.3: Multimodal Test Functions.

Figure 1.2 shows the Sphere and Sum Square functions that consist of only one dip in the centre of the mapping, which is called the global optimal value. However, figure 1.3 shows the Rastrigin and Michalewicz functions with one global optimum value, which is coloured with blue and many other dips in the mapped plane called local optimum values, making it multimodal.

Metaheuristic methods, with the help of exploration, explore the search area for the possible global regions and uses their exploitation skills to find the global optimum point in a global region which in WSN are the CHs positions. However, both the exploration and exploitation capabilities are sometimes not found in certain metaheuristic algorithms because of the algorithm's behaviour and parameters. The metaheuristic methods can be further categorised as non-hybrid methods and hybrid methods.

The hybrid metaheuristic method is the idea of combining components from different algorithms or search techniques to find the optimal solution (Blum & Roli, 2008). Hybrid methods used in CH selection and cluster formation, which have been used in recent years, have given great success in the field of WSN. This is because the capability of two distinct algorithms merging gives an added advantage of having a balance between exploration and exploitation to boost the performance in terms of energy efficiency, network lifetime and throughput (Kaur & Mahajan, 2018; Lavanya & Shankar, 2019; Rambabu et al., 2019; Shankar et al., 2016).

In WSN, the CHs are selected based on several objective functions, which are the fitness function for the metaheuristic algorithms to ensure the best position for a potential CH. The objective function that drives to select appropriate CH usually contains distance and energy constraints. Hence, a novel hybrid metaheuristic algorithm with a revised objective function is needed to avoid selecting inefficient CH, which will affect the stability and communication of the whole network. Besides, a proper hybrid metaheuristic method with good exploration and exploitation capability can alleviate the problem of limited power capacity.

1.2 Problem Statement

Using an innovation or formulation widely because of excellent performance will continuously need attention as new limitations and problems will be discovered and used in many applications. A similar situation can be seen in the research on WSNs as the usage of optimal WSNs rapidly grows in many applications, not only on a small scale but also in large-scale systems. So, despite the wide usage of WSN, it is still tied with many limitations, specifically in resolving clustering-related issues that arise with misuse and mismanagement of sensor networks.

The most prominent problems discovered in clustering WSN are hotspot or energy hole problems and isolated node problems. The hotspot problem is deemed to be the death of nodes near the sink quicker because of the high amount of traffic that it possesses, causing a network hole and simultaneously degrading the network performance and affecting the lifetime of the network. (Akbar et al., 2016; Z. Luo & Xiong, 2017). On the other hand, the isolated node problem occurs when the CHs are not selected appropriately in rounds before, which makes certain nodes not join any clusters and send data by themselves to the sink causing high energy usage because of the distance and reduced communication performances (Din et al., 2016; Leu et al., 2015). These issues disrupt the stability and inter-cluster communications in terms of network lifetime, energy consumption, frequency of re-clustering, total packet delivery, throughput, and end-to-end delay of clustered WSN. For a better picture of the problem, an illustration is given below:

In the early years, CH was selected based on selection criteria. A new calculation based on extra parameters such as energy and distance is made to select optimal CHs. However, these non-metaheuristic methods have the limitation of costly, high process and calculation time, and it needs strong assumption and effort on the structure of objective functions (Sergeyev et al., 2018). Besides, new cluster formation techniques called unequal

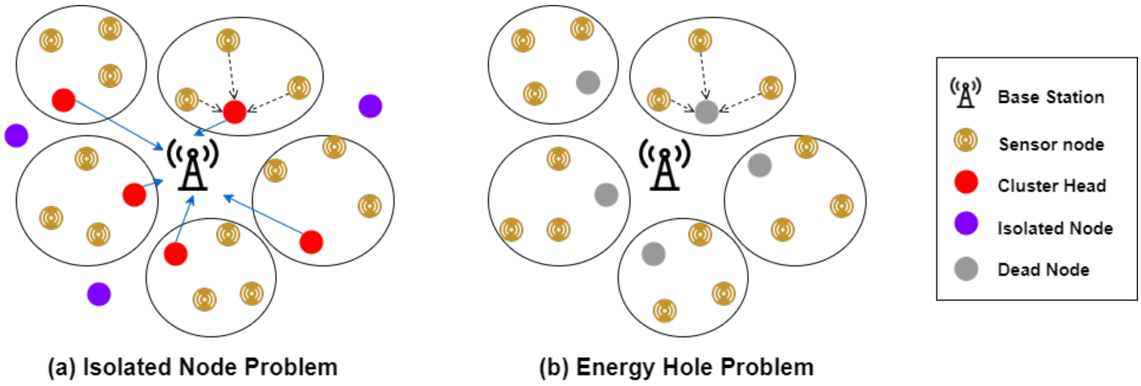

Figure 1.4: Problems Faced by Clustering in WSN.

clustering (Baniata & Hong, 2017; V. Gupta & Pandey, 2016) were introduced to solve the network hole and isolated node problems. These cluster formation techniques have reduced scalability, and it may require extensive planning for deployment as it is not a viable option for large-scale networks. So, this directly points to the appropriate selection of CH and optimal cluster formation using metaheuristic methods.

Metaheuristic methods are deemed to obtain good solutions in a reduced amount of time, and it is able to solve complex optimization problems (Xu & Zhang, 2014). Besides, metaheuristic methods are also easier to implement in large-scale networks and efficient in solving Large Scale Global Optimization (LSGO) problems (Mahdavi et al., 2015). To overcome these issues, a method with a good balance of exploration and exploitation is needed to obtain the global optimum solution for efficient CH selection and cluster formation. Some researchers propose hybrid metaheuristic methods to solve the aforementioned problem. A hybrid metaheuristic method combines two distinct algorithms' advantages into forming one new method (Ting et al., 2015). So, hybridization balances the exploration and exploitation capabilities, and it is also deemed to have reduced computational cost and implements efficient optimization (Xu & Zhang, 2014). Some past studies used the hybrid methods in CH selection and cluster formation phases of clustered WSN (R. Kumar & Kumar, 2016; Pitchaimanickam & Murugaboopathi, 2020;

A. Y. Prasad & Rayanki, 2019). However, the algorithms used to hybridize must be appropriately selected as some hybrid methods do not give a balance between exploitation and exploration capability, where it may promote more exploitation than exploration or more exploration than exploitation.

Swarm based algorithm such as Particle Swarm Optimization (PSO), Artificial Bee Colony (ABC), Ant Colony optimization (ACO), and Sperm Swarm optimization (SSO) tend to have more exploitation capability because it does not need prior knowledge and uses the fitness value of an individual to guide search whereas non-swarm based algorithms such as Genetic Algorithm (GA) and Gravitational Search Algorithm (GSA) tend to have strong exploration capability as the search is guided by gradient information (Cao et al., 2019). So, balancing the exploration and exploitation hybridization of a swarm-based and non-swarm-based algorithm may yield the best performance.

Hence, this calls for integrating two algorithms with good exploration and exploitation capabilities called the Sperm Swarm Optimization (SSO) algorithm and Genetic Algorithm (GA) to form a novel technique. SSO algorithm method is the concept based on the sperms travelling from a low-temperature zone to a high-temperature zone in search of an egg in a fallopian tube. The fallopian tube's region is considered to be the optimum value that the egg located in this area awaiting sperm (here, locating this area is considered as an optimal solution) which promotes exploitation capability (H. A. Shehadeh et al., 2018). Besides the GA is where the algorithm illustrates the natural selection process where the fittest people are selected for reproduction to produce next-generation offspring using mutation and crossover functions (the purpose of GA here is to find the global minimum or maximum of the objective function) which promotes exploration capability (Holland, 1992).

To provide a quality result and to improve the clustering of WSN, this hybridized optimization algorithm termed a Hybrid Sperm Swarm Optimization and Genetic Algorithm (HSSOGA) is utilized. As such, this study proposes a hybrid metaheuristic method for CH selection and cluster formation to ensure the stability and inter-cluster communication performance are enhanced in clustered WSN.

1.3 Research Questions

To draw the objectives of this research, there are some specific research questions to be asked as listed below:

i How to find the research gap that exists in the field of optimization?

ii How to achieve exploitation and exploration capabilities in metaheuristic method for global optimum solutions?

iii How to mitigate the isolated nodes and energy hole problem in clustered WSN?

iv How to ensure network stability and inter-cluster communication are enhanced in clustered WSN?

1.4 Research Objective

The main target of the research is to ensure the quality of a WSN is preserved with good CH selection and cluster formation in order to have optimal energy usage, longer network lifetime, higher packet transfer rate and higher network throughput. To achieve the main goal, some specific objectives are needed, as listed below:

i To explore the literature on metaheuristic methods in the field of optimization.

ii To develop a hybrid metaheuristic method that balances exploration and exploitation capabilities.

iii To enhance the cluster head selection and cluster formation by using the adaptive hybrid metaheuristic method.

iv To validate the proposed method used in clustering by evaluating the performance in terms of network lifetime, average residual energy, re-clustering occurrence, total packet delivery, network throughput and end-to-end delay.

1.5 Scope of Study

There are many challenges in the current WSN fields that require an optimal solution for CH selection and clustering process by maximizing the network lifetime and minimizing the energy consumption. The Metaheuristic method plays a major role in selecting the optimal CH to ensure that all the nodes are clustered into a cluster to avoid isolated node problems and ensures that the CH selected is not close to the BS to cause energy hole problems. Therefore, the metaheuristic method that searches the optimal position for CH in reference to the objective functions is a vital process in clustered WSN.

This research presents an extensive survey on the challenges associated with CH selection using specific selection criteria and the cluster formation process. In addition, the research studies the capability of developed hybrid methods with unimodal and multimodal test functions to ensure the usability of the proposed hybrid method in real-life scenarios and applications. To achieve the objective of selecting optimal CH, the exploration and exploitation of the hybrid methods are adaptively changed over time to ensure that the CH is considered based on the current fitness of the nodes. The performance of the proposed method is evaluated based on a standard-scale network. In this experiment, the network considers the standard area size of 100m x 100m with 100 nodes deployed. This work only considers clustering in WSN. The study ensures that the proposed method can reduce the isolated nodes and energy hole problems by enhancing the stability and inter-cluster communication of clustered WSNs. A summary flow of the research is depicted in Figure 1.5 below. Clustering using the hybrid metaheuristic method in data and text mining is reserved for future work (L. Bijuraj, 2013).

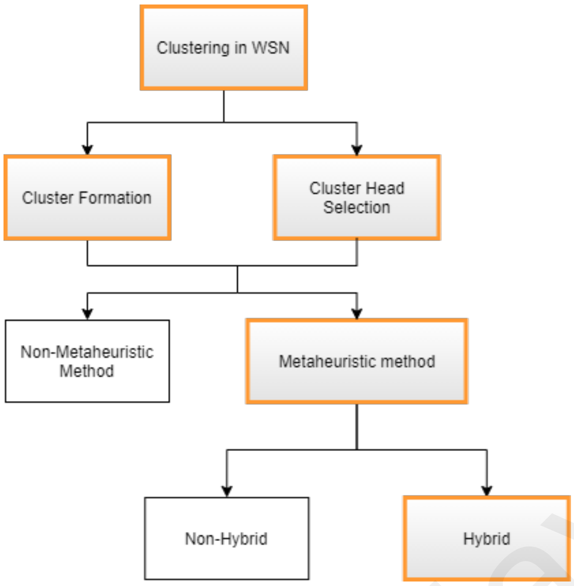

Figure 1.5: Summary flow of the proposed research.

1.6 Motivation and Contribution of the Study

The existence of new bio-inspired and nature-inspired algorithms motivates new research to test their functionalities. Some algorithms are unique, and altering their parameters will ensure better performance of the algorithms. As such, hybridizing new sets of algorithms will unlock the full potential of a certain algorithm to search for optimal solutions, such as the CH selection process. A flat network is the traditional WSN deployment where transmission happens in the form of flooding causing data redundancy. So, the flat network is inefficient in energy conserving compared to cluster-based WSN (Zeb et al., 2016). In clustered WSN, two vital phases are CH selection and cluster formation. Failure to have good CH selection may cause energy hole problems and may also lead to many re-clustering phases, which affects the stability of the network. Besides, a good cluster formation technique will mitigate the isolated node problem, keeping all the nodes' connectivity and communication efficient. So, using metaheuristic algorithms in WSN can greatly impact the performance of a system.

In applications such as disaster management, many international projects focus on using WSNs to facilitate response management and rescue lives because WSNs are efficient in sensing the environment and communicating to make smart decisions upon their observations (Benkhelifa et al., 2014). In addition, diseases that are connected to diabetes, asthma, heart failure, and memory declination are a threat to humans where WSNs plays a vital role in collecting information based on personal physical and behavioural states in real-time (Ko et al., 2010). When we talk about healthcare and real-time data, it is important to ensure the connectivity and lifetime of the sensors for an efficient data transfer so that precautionary steps can be taken immediately. The ability to enhance the lifetime and good connectivity of small sensor nodes can be done with the help of clustering using metaheuristic methods.

Since hybrid metaheuristic methods can improve the CH selection and clustering process, the appropriate algorithms must be chosen to be hybridized to unlock their maximum potential. In this study, we are motivated to select SSO and GA to be hybridized because of several reasons. PSO algorithm is an approach that has wide succession in the field of WSN in optimizing single-objective and multi-objective problems, but since it is a swarm-based algorithm, it tends to fall into local optimum easily without much exploration. Many CH selection approaches used PSO to enhance the energy efficiency and network lifetime (Pitchaimanickam & Murugaboopathi, 2020; Rao et al., 2017; Sangeetha & Sabari, 2018). In the year 2019, Shehadeh proposed an empirical study between PSO, GA, and the newly introduced SSO. The authors discuss that SSO outperformed PSO in four benchmarking testings, which are the Rosenbrock function, Rastrigin function, 2n Minima function, and EGGCrate function (H. A. Shehadeh et al., 2019). These four benchmark functions are deemed unimodal, showing that SSO has good exploitation capability.

Nevertheless, GA outperformed SSO in the Rastrigin and EGGCrate functions, which is a multimodal function where GA ranked higher than SSO when the best achievable values are compared (H. A. Shehadeh et al., 2019). These results show that GA has better exploration capability. So, hybridising two distinct capable algorithms, such as SSO and GA, is a possible way to balance out the exploration and exploitation capability to obtain global optimum solutions effectively without being trapped into local optima solutions. Moreover, the possibility of tuning the parameters of SSO and GA exists to ensure better adaptive exploration and exploitation towards WSNs' real-life scenarios, such as environmental monitoring and disaster management systems.

The ability to adaptively tune algorithms such as PSO and GA yields a better performance in obtaining the global solutions (Dong & Wu, 2009; Iwasaki et al., 2006). This motivates us to utilize the hybrid metaheuristic method that can be adaptively tuned to suit the real-world WSN scenarios for efficiency in terms of network performance with appropriate CHs selection. The contribution of the research can be described as follows:

- The exploration and exploitation abilities are ensured to be equally present in a single algorithm to obtain global solutions. This is to ensure that the method is able to solve both unimodal and multimodal test problems by obtaining global optimal in the form of a hybrid method which is easier to implement and cost-effective.
- The adaptive exploration and exploitation capabilities selecting the appropriate CH will help efficiently alternate between exploration and exploitation processes to find the global solutions. This ensures that the algorithm studies the fitness value of the population and adjusts the parameters to suit the search process.
- CH selection will be based on a more refined objective function with the inclusion of isolated node probability objective. This will ensure that the CH is selected not

close to the BS and considers the global optimum value towards a region that allows nodes far away from BS to join a cluster.

- Two enhanced clustering methods are used for clustering where (1) in enhanced LEACH clustering, re-clustering occurs every 10% drop in the average energy level compared to the previous round's average energy level whereas (2) in another method, the re-clustering will be triggered only when a node completely dies. This will limit unnecessary changes in the cluster head, which will exhaust the energy of the nodes. In addition, it also ensures that the node's energy is balanced and a longer network lifetime is preserved.

1.7 Organization of Thesis

The introduction to the research is given to ensure that the readers get a summary of the entire research and experiments. The given objective, scope and motivation of the research show the direction and focus of the research. As such, the remainder of the thesis chapters are organized as below:

Chapter 2 describes the conventional clustering protocol, LEACH. The explanation includes the mechanics and process of the protocol. Besides, the introduction to the modified LEACH protocols and other clustering protocols with their objective function details are outlined. The methods that use non-hybrid and hybrid metaheuristics to select CH and form clusters are also briefly described in this chapter.

Chapter 3 shows the details of the methodology of the research. A detailed explanation of the objectives and their connection is given. The description of selected models, test functions and parameters are explained too.

Chapter 4 shows the development of the proposed HSSOGA method. In addition, the method and procedure of its conventional method are also outlined in detail. The performance of the proposed method with conventional and existing hybrid methods is evaluated and detailed in this chapter.

Chapter 5 shows the implementation of the developed HSSOGA in the clustering of WSN. An explanation of adaptive exploration and exploitation by adaptive parameter tuning is given. Furthermore, HSSOGA with adaptive exploration and exploitation is evaluated and compared with the existing hybrid metaheuristic method in clustered WSN to show the performance in terms of network stability and inter-cluster communication.

Chapter 6 discusses the results obtained in Chapter 5. A complete description and explanation of the advantages and disadvantages of the proposed method are given as well.

Chapter 7 concludes the thesis with an overall remark, revisiting the objectives and contributions and stating the future directions.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

The literature review is a published overview of the papers in the journal, books, and other documents where the literature is managed into subtopics for better viewing. The literature review is necessary to remove the redundancy of the study, helps to improve research writing and helps to develop many research skills (Creswell, 2012). Therefore, understanding the background of WSN and how it works is an important task to understand the overall research presented in this chapter from section 2.2 onwards. The CH selection and cluster formation phase in clustering WSNs is facilitated by either selection criteria (non-metaheuristic methods) or metaheuristic methods. Therefore, a good balance between exploration and exploitation capability has been suggested in order to obtain optimal global solutions without being trapped in local optima. Nevertheless, metaheuristic methods rely on the defined objective functions to obtain global solutions. Metaheuristic method with good exploration and exploitation capability with well-refined objective functions is one of the important parameters in an optimization model, which serves as the main topic of this thesis. A detailed discussion on various metaheuristic and non-metaheuristic methods used in WSN is discussed in detail to ensure the advantages and disadvantages of the method used. This chapter discusses the earliest clustering protocol called Low-Energy Adaptive Clustering Hierarchy (LEACH) and its modified or extended versions in section 2.2, followed by existing non-metaheuristic methods, existing non-hybrid and hybrid metaheuristic methods in WSN in section 2.3, 2.4 and 2.5 respectively. Section 2.6 discusses some metaheuristic methods used in the optimization of test functions and other fields of study. Finally, literature based on adaptive tuning of parameters in metaheuristic methods is also discussed in section 2.7. Section 2.8 provides a small discussion on the importance of clustering, followed by a brief chapter summary in section 2.9.

2.2 Low-Energy Adaptive Clustering Hierarchy (LEACH)

LEACH method is used in a network made up of cheap and energy-efficient microsensors to achieve better quality results in large-scale networks (W. R. Heinzelman et al., 2000). LEACH organizes itself by using adaptive clustering, cluster head rotation, and local computation to have a balanced energy distribution in the network. There were two assumptions made in this research, which are (1) the base station is stationary and located far away from the sensor nodes, and (2) the sensors in the field are homogeneous and energy-constrained. Recent research has also evaluated LEACH-based clustering in heterogeneous and mobile scenarios (Khandnor & Aseri, 2017; Sujee & Kannammal, 2015). LEACH consists of two crucial phases, which are the set-up phase and the steady-state phase. The steady-state phase is longer in comparison to the set-up phase, the aim of which is to minimize overhead. In LEACH, the CH is typically selected first before the clusters are formed. Still, it is not the same for all the existing clustering methods, as some researchers tend to improve the objectives by performing cluster formation first, such as (Abdolkarimi et al., 2018). The overview of LEACH is shown in Figure 2.1. In LEACH, the cluster head is selected before the cluster is formed.

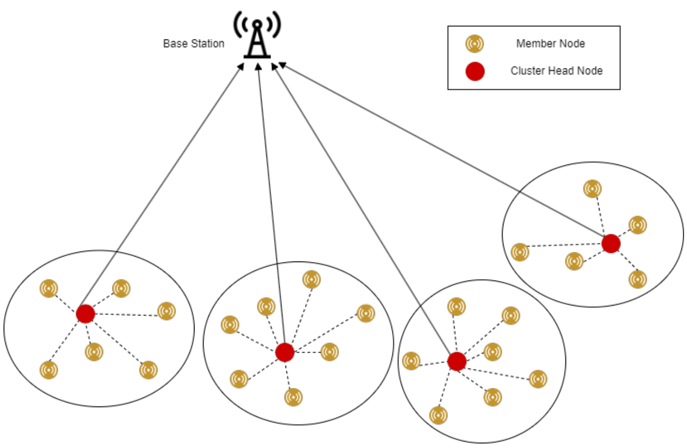

Figure 2.1: The Overview of LEACH.

In the advertisement phase, the CHs are elected first using a threshold based on the suggested percentage of CHs in the network and the number of times a node has been a CH. The threshold T(n) is computed as (W. R. Heinzelman et al., 2000):

$$T(n) = \begin{cases} \frac{P}{1-P\left(r mod \frac{1}{P}\right)}, & \text{if } n \in G \\ 0, & \text{otherwise} \end{cases} \tag{2.1}$$

Where P is the suggested percentage of cluster head, r is the current round, and G is the set of nodes that have never been cluster heads in the last $1/P$ rounds. The threshold ensures that every node will become CH at least once. After all the nodes have become CH at least once, which is after $1/P$ rounds, all the deployed nodes will be eligible again to be a CH for the second time. The elected cluster head will then broadcast an advertisement message through carrier-sense multiple access (CSMA) MAC protocol to the non-CH nodes for them to decide which cluster belongs to that node in that round. The cluster joining decision is based on the largest signal strength received from a CH because it will take minimum energy for communication. However, a non-CH node can receive two similar signal strengths from two CHs. In this case, it will choose a random cluster head between the two CHs. The non-CH node must send a cluster joining message to its cluster's CH through the CSMA MAC protocol in the cluster set-up phase. Upon receiving the joining information of the nodes in its cluster, the CH then schedules a time slot for each node to transmit by using time-division multiple access (TDMA) to avoid collision during the transmission period.

After these phases, data transmission can commence. Data transmission is done over the sensor's radio channel by using a first order radio model (W. R. Heinzelman et al., 2000) with certain characteristics, as shown in Table 2.1.

Table 2.1: The radio characteristics and its values used in LEACH (W. R. Heinzelman et al., 2000).

Operation	Energy Dissipated
Transmitter Electronic ($E_{Tx-elec}$) Receiver Electronic ($E_{Rx-elec}$) ($E_{Tx-elec} = E_{Rx-elec} = E_elec$)	50 nJ/bit
Transmit Amplifier (ϵ_{amp})	100 pJ/bit/m2

The equations for the transmission phase are as such (W. R. Heinzelman et al., 2000):

$$\begin{aligned} E_{Tx}(k,d) &= E_{Tx-elec}(k) + E_{Tx-amp}(k,d) \\ E_{Tx}(k,d) &= E_{elec} * k + \varepsilon_{amp} * k * d^2 \end{aligned} \tag{2.2}$$

The equations for the receiving phase are as such (W. R. Heinzelman et al., 2000):

$$\begin{aligned} E_{Rx}(k) &= E_{Rx-elec}(k) \\ E_{Rx}(k) &= E_{elec} * k \end{aligned} \tag{2.3}$$

Where E_{elec} is the energy dissipated by transmission and reception, ε_{amp} is the amplification factor of the transmission, k is the number of bits of a message, and d is the distance of transmission. There are some assumptions taken into consideration in applying the first order radio model, which are (1) the radio channels are symmetric, and (2) data are always sensed, which makes the system not an event-driven sensing type. An overview of the LEACH radio model is shown in Figure 2.2 (W. R. Heinzelman et al., 2000).

2.2.1 Advantage and Disadvantage of LEACH

LEACH has been a big contributor to the field of WSN with its clustering technique to enhance the network lifetime and reduce energy consumption. Even though in the year the 2000s, LEACH seemed to show huge growth in WSN, there were some limitations that followed it when researchers were actively proposing and developing new solutions to it. The advantages of LEACH include:

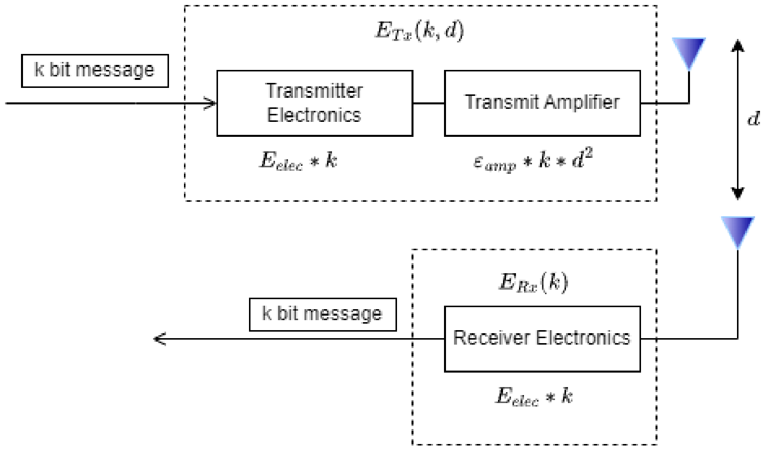

Figure 2.2: First Order radio model used in LEACH (W. R. Heinzelman et al., 2000).

1. Balanced energy dissipation: LEACH protocol allows all the nodes to compete to be the CH based on the predefined criteria at a time that is divided into rounds. So, every node has an equal probability of becoming CH and relatively has balanced energy dissipation among the nodes (Yun et al., 2011).
2. Reduced control messages overhead: All the nodes have an autonomous decision to become a CH based on the selected criteria, and the intervention of BS is not needed. This ensures that the control overhead messages are reduced, which indirectly reduces the excessive overhead energy consumption of the network (Ouadi & Hasbi, 2020).
3. Enhanced data aggregation. LEACH ensures that uncorrelated noises are reduced by combining several unreliable data to enhance the common signal by producing a more accurate signal with the received data. So, this ensures that CHs aggregate data as a whole, relatively reducing the traffic of the entire network (Rajesh et al., 2017).

The disadvantage of LEACH include:

1. Poor data transmission mechanism: When a CH dies, the data carried by the particular CH will never reach its destination (base station), making the whole cluster

useless (Gill et al., 2014).

2. Random election of CH: In LEACH, the CH are elected based on a rotational basis to ensure all the nodes participate in becoming a CH. So, this can cause a low energy node to be selected as CH, which will deteriorate the network lifetime quickly (Bharany et al., 2021).

3. Unbalanced clusters and position of CH: Since random CHs are selected, LEACH does not guarantee the number of clusters because cluster formation is also done randomly, which makes the distribution of clusters unbalanced. Besides, the positioning of CH is also not guaranteed as some can reside in the centre of the cluster and some at the edges. These consume more energy when it comes to intra-cluster communication, which affects the network's overall performance (Awad et al., 2012; Bharany et al., 2021).

2.2.2 Modified/Extended Versions of LEACH

In 2017, Khandnor and Aseri proposed a threshold distance-based clustering routing protocol taking into consideration both mobile and non-mobile environments in (Khandnor & Aseri, 2017). The method is based on LEACH as it is called LEACHDistance for the static environment and LEACHDistance-M for the mobile environment. CH selection criteria in this protocol are split according to the static and mobile scenarios. In a static setting, the upper threshold distance, lower threshold distance, and remaining energy of the node are taken into consideration. On the other hand, in a mobile setting, an extra criterion of low velocity of node (least mobile node) is given attention so that the CH can efficiently communicate with its members. During simulations, LEACHDistance-M performed better than the LEACHDistance and other methods that were compared in terms of network lifetime, correlation, coefficiency, scalability, number of data packets received by the BS, and energy efficiency.

The authors in (Dongare & Mangrulkar, 2016) proposed an optimal cluster head selection method for defending gray hole and black hole attacks in WSNs. The method is based on LEACH, known as LEACH-Attack Defense (LEACH-AD). Gray hole attacks are where malicious nodes block the passage of the packets in the network, while black hole attacks are where trustworthiness is exploited to route the packets to the wrong path. These problems are tackled by implementing a good CH selection technique in a multi-hop data transfer environment, where a CH is selected by detecting the nodes that are already compromised and choosing the node with maximum energy from the non-compromised node for a better lifetime of the network. The proposed technique performs better against attacks than existing techniques in terms of packet delivery ratio (PDR), throughput, and end-to-end delay at several intervals.

Some researchers prefer to modify LEACH in WSNs, where the authors in (Zhao et al., 2018) introduced a modified LEACH algorithm (LEACH-M). LEACH-M utilizes the network address and residual energy in selecting the best CH to tackle the unreasonable cluster head selection. Moreover, a cluster head competitive mechanism is integrated into LEACH-M, where the average energy E_{aver} is calculated, and the current residual energy E_{res} of a node is compared with it to select the CH. This technique prevents nodes from running out of energy quickly and maintains the WSN structure for a more extended period than some existing methods.

In 2020, the authors in (Wu et al., 2020) proposed a many-objective optimization model in WSNs based on LEACH, termed LEACH-ABF. There are four objectives considered in this model, which are cluster distance, the sink node distance, the overall energy consumption of the network, and the network energy consumption balance to select the cluster head. Balance function strategy, genetic operation, and penalty-based boundary intersection selection strategy (PBI) are introduced to achieve the true Pareto front, better search capabilities, and enhance convergence and diversity, respectively. The whole network was also designed based on the multi-hop model and tested with the DTLZ test suite, which showed that LEACH-ABF has better distribution and convergence as well as balanced energy consumption compared to some existing multi-objective algorithms.

The energy consumption problem in WSNs has been researched until recently as Pour and Javidan proposed a new energy-aware cluster head selection method for LEACH (DRE-LEACH) in (Pour & Javidan, 2021). Four CH selection criteria are imposed in this method, namely, residual energy, the distance between sink nodes and the centrality of the nodes, and the number of neighbours of each node. A threshold value is calculated by the ratio of the number of CH with the number of alive nodes, where it is ensured that a node becomes CH only when the threshold value is below 0.05 to control the number of CHs that exist in the network at one time. DRE-LEACH outperforms other existing LEACH-based protocols in terms of network lifetime and reliability.

Table 2.2: Comparison of previous modified/extended version of LEACH

Method (Author)	**Objective(s)**	**Selection Criteria (Objective Function)**	**Advantages**	**Limitations**
LEACH-Distance-M (Khandnor & Aseri, 2017)	Improve network load balance. Improve network lifetime.	Upper threshold distance, lower threshold distance, remaining energy, and least mobility.	Discusses both static and mobile environments. The hotspot problem and single hop transmission problem are analysed.	Usage of many criteria may increase the computation calculation.

Continued on next page

Table 2.2, continued

Method (Author)	**Objective(s)**	**Selection Criteria (Objective Function)**	**Advantages**	**Limitations**
LEACH-AD (Dongare & Mangrulkar, 2016)	Improve energy efficiency. Improve security defence of WSN.	Energy	Focuses on security attacks on WSN. The honest nodes are also determined to be entrusted as cluster heads during the packet transmission phase.	The algorithm is complex, and the process will be time-consuming.
LEACH-M (Zhao et al., 2018)	Balance the network energy burden.	Residual energy and network address of nodes	A CH competitive mechanism is focused on mitigating the communication energy cost. The ex-cluster head avoids running out of its energy and still serves as a "subordinate" for the new "commander" after becoming an ordinary child node.	Does not discuss the hotspot problem that it will face. Will face problems storing the network address of nodes if the network is huge.
LEACH-ABF (Wu et al., 2020)	Balanced energy. Extend network lifetime.	Cluster distance, sink node distance, overall energy consumption, and network energy consumption balance	ABF adaptively combines the diversity and convergence functions. It uses genetic operations to produce better solutions so that the optimal solution can be found more efficiently in the solution space. The computational complexity of the algorithm is also discussed.	Including three other methods will increase the overall complexity of the algorithm. LEACH-ABF does not converge well in multi-modal problems.
DRE-LEACH (Pour & Javidan, 2021)	Reduce the energy consumption. Improve network lifetime.	Residual energy, the position and centrality of nodes	A variable range is used to localize the required calculations, which leads to less computation.	The involvement of many calculations to determine the nodes' score that will consume more energy.

2.3 Non-Metaheuristic Algorithms in WSN

The authors from (Leu et al., 2015) proposed an energy-efficient clustering scheme to prolong the network lifetime. The authors focused closely on the traditional LEACH protocol and implemented a regional energy-aware clustering method with isolated nodes (REAC-IN). Isolated nodes are considered one of the problems faced by clustering, where some nodes do not join any cluster and tend to transfer data directly to the BS due to the random selection of the CH. Given the issue, the CH selection in this approach is made based on residual energy and regional average. The authors later discuss the data transmission of the occurring isolated node, where it uses a first-order radio model, where it is still possible for the isolated nodes to exist. In a comparison of REAC-IN with LEACH and other clustering algorithms, REAC-IN performed better in terms of network lifetime and stability of the network.

Later in the year 2016, ((V. Gupta & Pandey, 2016) proposed an improved energy-aware distributed unequal clustering protocol (EADUC) in a heterogeneous and multi-hop environment. Improved EADUC considers a number of neighbours, the distance between the nodes and the BS, and the residual energy in deciding the competition radius for the cluster formation. The main idea of employing non-uniform clustering is to solve the energy hole problem. The proposed method is then tested with three scenarios where the placement of nodes is varied. The simulation results show that the improved EADUC outperformed the non-improved version in terms of network lifetime and energy consumption. Even though it is an effective method to have an efficient clustered WSN, it takes a lot of effort and includes many other methods to show its performance.

In 2017, (Z. Luo & Xiong, 2017) conducted a design and analysis on the energy balance clustering technique (EBC). The CH is selected using an improved threshold value, where the energy level of nodes and distance to sink are considered. The authors considered using multi-hop communication in the research as it can reduce energy consumption. In this case, the CH near the sink will die quickly due to heavy traffic loads. So, the usage of the relay node is introduced to overcome the hotspot problem. EBC yielded better performance in terms of the number of messages received and average energy consumption compared to existing protocols.

The authors in (KHEDIRI et al., 2017) proposed a technique for selecting CHs based on residual energy, neighbour degree, and distances among CHs, named the fixed competition-based clustering approach (FCBA). In FCBA, a hello message is sent to explore the neighbourhood, and then each node calculates and distributes its weight; the node with the smallest weight becomes the CH, and the other nodes settle down to become the member nodes. The authors implemented this technique in a multi-hop environment and compared it with several existing techniques. The proposed technique seems to be effective in balanced energy consumption and improving network lifetime.

The authors in (Feng et al., 2018) proposed the selection of cluster heads dynamically for monitoring in WSNs, using an efficient target tracking approach termed ETTA. In ETTA, four CHs that are at the edge of the clusters are chosen, and the clusters are further divided into four sub-areas. A collecting cluster head (CCH) is selected, making it a multi-hop data transmission environment, where it collects the data from CHs, aggregates, and sends it to the BS, which greatly reduces the data gathering costs. The CCH is typically chosen based on the residual energy and lowest distance to the sink. The simulation proved that ETTA outperformed the state-of-the-art approaches by having a better network lifetime and lower energy consumption.

Zahedi proposed a clustering protocol closely related to LEACH by applying weighting coefficients termed (CWC) in (Zahedi, 2018). The main difference between the proposed algorithm and LEACH is that it uses weighted residual energy and distance from the sink threshold to select the appropriate CH. In this literature, the clusters are formed first, and then the suitable CHs are chosen for each cluster. This research considers two scenarios in terms of smaller and slightly bigger network dimensions. From the comparison, it was observed that CWC shows dominance in terms of global performance compared to some existing methods.

In the year 2019, the authors in (Darabkh et al., 2019) proposed two CH selection techniques which are energy and distance-based cluster head selection (EDB-CHS) and EDB-CHS with balanced objective function (EDB-CHS-BOF). The authors considered that the cluster area has a hexagonal shape which is near to the reality in a single-hop data transfer model. For the CH selection, a threshold probability is created by ensuring that the node with higher residual energy, lesser energy consumption, and the shortest distance between the sensor node and the BS is selected. In the second technique, the objective function is added to select better CHs by including the expression of node optimal probability. EDB-CHS-BOF performed better than EDB-CHS and other protocols in terms of network lifetime, balanced energy consumption, and total data delivery.

In the same year, Alami and Najid proposed an enhanced clustering hierarchy (ECH) approach to maximize the lifetime of WSNs in (El Alami & Najid, 2019). Initially, the sleeping and waking nodes are determined, and the CH is selected randomly from the waking nodes. The re-selection of the CH uses residual energy and local distance as selection criteria. By implementing sleeping and waking nodes, the wastage of energy without transmission is reduced dramatically in a multi-hop network. However, it does not apply to some applications with consistent data transmission, such as environmental sensing nodes. The proposed method managed to reduce the data redundancy of overlapping nodes and maximize the network lifetime compared to other existing protocols.

The authors in (Zeng et al., 2019) proposed an Energy-Coverage Ratio Clustering Protocol (E-CRCP) to be used in heterogeneous energy network environments. In this, the optimal numbers of clusters are determined first by calculating the total energy used in communication. Next, the CH is selected based on the maximum coverage ratio so that the CHs are evenly distributed throughout the network. Then, the CH that consumes a large amount of energy is replaced in the next communication iteration. Comparing E-CRCP with other existing protocols showed that E-CRCP improves network lifetime, balances the network load, and reduces the energy consumption in heterogeneous WSNs.

In the year 2020, the authors from (Umbreen et al., 2020) proposed a CH selection method based on a mobile sensor environment named Energy-efficient mobility-based cluster head selection (EEMCS). In EEMCS, the cluster head is chosen based on residual energy, mobility, distance to the base station, and neighbours' count, with the inclusion of weightage as below:

$$Weightage = \frac{E_r * w1 + Degree * w2}{ML * w3 + D_{toBS} * w4} \tag{2.4}$$

E_r is the residual energy, $Degree$ is the neighbor degree, ML is the mobility level, and D_{toBS} is the distance from CH to BS, whereas $w1$, $w2$, $w3$, and $w4$ are the corresponding weightages, respectively. EEMCS performed better in terms of network lifetime, energy consumption, average energy, and throughput when compared with several existing algorithms.

Following the trend of using coefficients in CH selection, Turgut proposed a cluster head selection method called dynamic coefficient-based adaptive cluster head selection

(DCoCH) in WSNs (Turgut, 2020). The selection criteria that are used to select CHs are the residual energy of the nodes, the intra-cluster communication cost, and the number of neighbours. The coefficients applied are dynamically changed from 1st round to FND, then to HND, and finally to LND. DCoCH outperformed two other adaptive-based CH selection methods in terms of prolonging network lifetime.

The authors in (Hassan et al., 2020) proposed another network lifetime prolonging method named improved energy-efficient clustering protocol (IEECP). In IEECP, the optimal numbers of balanced clusters are determined first by using a mathematical model and the modified fuzzy C-means algorithm (M-FCM), which considers the overlapping case and multi-hop communications. Then, CH selection and CH rotation are introduced by integrating the back-off timer called CHSRA. The backoff timer is used in the CH selection phase as it reduces the overheads of the nodes. Moreover, during the cluster rotation phase, the unbalanced energy consumption problem is tackled by threshold values using the energy consumed and the ratio from the initial energy. From the evaluation, it can be observed that the proposed method performed better than some existing methods in terms of balanced energy consumption and improved network lifetime.

Table 2.3: Comparison of the non-metaheuristic method used in WSN.

Method (Author)	**Objective(s)**	**Selection Criteria (Objective Function)**	**Advantages**	**Limitations**
REAC-IN (Leu et al., 2015)	Prolong network lifetime.	Residual energy and the regional average energy	Focuses on isolated nodes. Uses regional average energy and the distance between sensors to determine the data transmission for efficient data transmission.	The calculation of regional energy will increase the processing time. Usage of regional energy will still exhaust the individual energy quickly.

Continued on next page

Table 2.3, continued

Method (Author)	Objective(s)	Selection Criteria (Objective Function)	Advantages	Limitations
EADUC (V. Gupta & Pandey, 2016)	Increase network lifetime.	Residual energy, distance, number of neighbour nodes	Improves network lifetime. Focuses on energy hole problem. It uses a different competition radius rule for producing unequal clusters to reduce energy consumption.	Assigning different competition radii will take more effort and time of deployment. It is also not very scalable in terms of number of nodes after deployment.
EBC (Z. Luo & Xiong, 2017)	Balanced Energy Consumption	Sensor nodes' the energy level and distance to the sink.	Focuses on giving a balance of energy consumption to the CH nearer to the BS. Focuses on hotspot problem.	The probability of signal collision and interference is ignored. The method consumes more energy when it is iterated for more rounds.
FCBA (KHEDIRI et al., 2017)	Minimize energy consumption.	Energy, degree, and distance	Global sensor information is available for efficient clustering.	It will contribute to the energy hole problem. The interference is ignored.
ETTA (Feng et al., 2018)	Balance energy consumption. Increase energy efficiency.	CH location and residual energy	CH is dynamically chosen on the edge of a cluster. CCH is used to collect the sensed data where the data are aggregated near to the data source and the transmitting data are decreased. Cluster maintenance is discussed.	Organizing the network into clusters makes forming the network difficult and time-consuming. The selection of CH and CCH will increase the selection time. LEACH still performs better in terms of transmission delay.
CWC (Zahedi, 2018)	Increase energy efficiency.	The residual energy of each node by applying weighting coefficients and distance from the sink	Focuses on energy efficiency. Weighting coefficients are used for optimal CH selection.	The coefficient greatly affects the results, so it needs more effort to be selected carefully. The complexity of the proposed algorithm in the CH selection process is higher.

Continued on next page

Table 2.3, continued

Method (Author)	**Objective(s)**	**Selection Criteria (Objective Function)**	**Advantages**	**Limitations**
EDB-CHS citeRN488	Balancing energy consumption. Extend network lifetime.	Residual energy, distance, and node's optimal probability	A tight closed-form expression is proposed for the optimal number of cluster heads (CHs). Deriving a new optimal probability for a sensor node to serve as a CH for EDB-CHS-BOF protocol for the reason of achieving a balanced energy consumption. The clustering shape used is hexagonal as it is closer to reality.	The involvement of many operations will increase the overall complexity of the algorithm. Having adjacent CHs will cause long-distance communications, which lead to increased energy consumption.
ECH (El Alami & Najid, 2019)	Maximize energy efficiency. Maximize network lifetime. Minimize data redundancy.	Energy and local distance	Focuses on maximizing the network lifetime by minimizing data redundancy (Sleeping and waking node). The accuracy and complexity of the algorithm are evaluated.	Random selection of CH, in the beginning, will select the CH with less energy which will cause the node to die quickly.
E-CRCP (Zeng et al., 2019)	Minimum energy consumption. Regional coverage maximization.	Residual energy and coverage ratio	Focuses on getting maximum coverage by considering the coverage ratio for CH selection.	The execution time will be increased due to more CH calculations.
EEMCS (Umbreen et al., 2020)	Reduce energy consumption. Prolong the lifetime of WSN.	Node's mobility level, residual energy, distance to sink, and density of neighbours	Focuses and explains re-clustering cases. The analysis is made in various network sizes and a varying number of nodes.	Selecting the appropriate weight for each parameter in CH selection will be difficult as it may affect the whole system.

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Table 2.3, continued

Method (Author)	Objective(s)	Selection Criteria (Objective Function)	Advantages	Limitations
DCoCH (Turgut, 2020)	Enhance network lifetime.	Intra-cluster communication cost, number of neighbouring nodes, and remaining energy	Due to the usage of time-based clustering, desired parameters are guaranteed to be elected as CHs. Time-division multiple access (TDMA) and code division multiple access (CDMA) is used to avoid collisions.	The alterations of coefficients can be tedious and may cause network stabilization issues. Must accurately set the coefficients for different applications.
IEECP (Hassan et al., 2020)	Prolong Network lifetime.	Energy consumed and the ratio from the initial energy	A new integration of the back-off timer mechanism for CH selection is used to reduce energy overhead. Forming balanced clusters that reduce the cost in the intra-distance based on a modified fuzzy C-means algorithm.	Usage of many functions and the number of CHs may increase the complexity of the overall algorithm. The execution time will be increased as well.

2.4 Non-Hybrid Metaheuristic Algorithms in WSN

The non-hybrid metaheuristic uses its original theory to achieve the best solution in WSN. In WSN, the non-hybrid metaheuristic algorithms can be categorized into two categories called conventional and modified or extended. The conventional non-hybrid metaheuristic algorithms are methods that do not alter the original algorithm, and it is used as it is, but the modified or extended includes certain modifications or adjustments to the original method for enhancement. Literature of both categories is discussed below.

2.4.1 Conventional

In the year 2016, the authors in (Vimalarani et al., 2016) proposed an enhanced PSO-based clustering method for energy optimization termed EPSO-CEO in a multi-hop data transmission environment. PSO is a theory based on the movement of particles where the position and velocity are updated till the global best solution is reached. The literature discusses cluster formation and CH selection based on centralized clustering by using PSO. A CH is selected based on the fitness function that involves the distance and energy using PSO, where the global best value achieved by PSO will be the CH of the particular cluster. The authors also precisely discuss inter-cluster and intracluster multi-hop data transmission using distance and residual energy. The simulation showed that EPSO-CEO performs better by minimizing energy consumption and enhancing the network lifetime when compared with other competitive methodologies.

Mann and Singh, on the other hand, proposed another clustering and routing method for energy efficiency using artificial bee colony (ABC) in (Mann & Singh, 2016). In this literature, ABC is used in a multi-hop and static environment. ABC is used in CH selection based on a fitness function that contains residual energy, the distance between CH and BS, and the distance between CH and CH as functions. ABC is then used to obtain optimized routing to have the least energy dissipation through communication. From the simulations, it could be observed that ABC performed better in terms of packet delivery, energy consumption, and throughput as compared to other algorithms.

Since bio-inspired algorithms tend to have fast convergence compared to non-metaheuristic methods, more studies were conducted on metaheuristic methods. In 2017, the authors in (D. Prasad et al., 2017) proposed a bio-inspired algorithm named firefly cluster head selection algorithm (FFCHSA). FFCHSA uses the fitness function based on energy, packet loss ratio, and end-to-end delay to select the CH in a multi-hop WSN, as discussed by the author in the introduction. From the simulations, it was seen that the proposed algorithm improves the overall performance compared to PSO and genetic algorithm (GA).

In the year 2017, a new metaheuristic algorithm was introduced by Jadhav and Shanker, called whale optimization algorithm (WOA) for CH selection, termed WOA-C (Jadhav & Thangavelu, 2017). WOA uses the concept of the hunting behaviour of humpback whales, where the random or optimal search is used to hunt the prey (exploration) and a spiral bubble-net attacking mechanism is used to catch the prey (exploitation). The CH is chosen based on the node that has the highest fitness value, where the fitness function considers residual energy and the number of neighbours for fitness calculation. From the simulations, WOA-C outperforms some contemporary existing protocols in terms of increased throughput, network lifetime, and stability period.

Wang and Zhu were inspired by the usage of metaheuristic algorithms in WSNs and proposed a chicken swarm optimization (CSO) algorithm. CSO was introduced in (Q. X. Wang & Zhu, 2017) with the idea of having classification as a rooster (CH), hen, and chicken, where the highest fitness value is the rooster, and the lowest fitness value is the chicken, and others are marked as hens. However, CSO is found to have a probability of the algorithm falling into the local optimum. As such, the levy flight method is added to improve diversity and ensure global search capability. The fitness value to choose the CH is based on the energy consumption factor, the distance between CH and BS, and point cluster compactness. The evaluation of the algorithm shows that CSO outperformed LEACH by enhancing the network's lifetime.

In 2018, the authors of (Ahmad et al., 2018) proposed a honeybee algorithm to select CHs in a mobile WSN (BeeWSN). In this, the selection criteria of CH selection are based on the remaining energy of the node, degree, speed, and direction. In the honeybee algorithm, two types of bees are identified, the onlooker and employed bees. The onlooker bees are the control packets that search for the most suitable CH by using the selection criteria, while the employed bees are data packets. This algorithm is deemed to have good exploration in the form of onlooker bees and exploitation in the form of employed bees. From the simulations, it was seen that BeeWSN forms more balanced clusters compared to some existing methods.

Metaheuristic algorithms are also used to optimize WSN QoS as proposed by (H. A. Shehadeh et al., 2018). The authors were inspired by the fertilization procedure in a female reproductive system and created the algorithm named Sperm Swarm Optimization (SSO). The theory of SSO is based on the sperms moving towards an egg (ovum) where only one out of millions will fertilize the egg with the presence of temperature and pH values. This theory can be translated as the one sperm that was able to fertilize is deemed to be the global optimum solution. WSN QoS considered in this work were end-to-end delay, end-to-end latency, energy efficiency and network throughput metrics. The results showed that the algorithm performed well in optimizing these models. Following the success of introducing the algorithm in the year 2019, the authors compared the results from optimizing six benchmark test functions of the proposed SSO with several existing algorithms (H. A. Shehadeh et al., 2019). The results obtained clearly shows the upper hand of the proposed SSO compared to other algorithms, which makes the algorithms.

In the year 2019, the authors of (J. G. Lee et al., 2019) proposed sampling-based spider monkey optimization and energy-efficient cluster head selection (SSMOECHS). This method was proposed to solve the location-based CH selection approach problems. Spider monkey optimization (SMO) is based on monkeys searching for food with good exploration capability. The CH is selected based on the sampling method of SMO, where coverage and energy of notes are considered as the objective function that must be maximized. The method is simulated through a homogeneous and heterogeneous environment by adopting multi-hop data transmission, which shows that SSMOECHS improved network lifetime and energy efficiency.

In the year 2019, a new bio-inspired algorithm based on earthworm breeding in nature named earthworm optimization algorithm (EWA) was proposed in (Pasupuleti & Balaswamy, 2019). In this algorithm, there are two types of nodes which are normal nodes and advanced nodes, where advanced nodes contain greater energy than normal nodes. EWA is used to select the optimal CH according to the highest fitness value based on energy and the distance between CH and nodes. In EWA, there are two types of breeding, where the first type is reproduction by a single earthworm, and the second type is reproduction by varying numbers of parents and offspring. From the simulation, it was observed that EWA performed better in terms of delay, throughput, network lifetime, and energy consumption compared to GA and PSO.

In 2019, the usage of metaheuristic algorithms seemed to give the best solutions in CH selection, so the authors in (Nayak et al., 2019) proposed a genetic algorithm (GA) based CH selection technique. A genetic algorithm is made with the concept of mutation and selection of chromosomes (Holland, 1992). The fitness function of the nodes is calculated based on the distance of each sensor to the CH and the total distance from sensors to the BS and the CH. Since the fitness function in this paper does not focus on energy metrics, there is a high possibility of selecting a CH with a low energy level which will cause problems later. From the simulations, GA was able to extend the network lifetime by having a balanced load among the nodes as compared to K-Means and LEACH algorithms.

Pathak proposed a proficient bee colony-clustering protocol (PBC-CP) in (Pathak, 2020). The concept of a bee colony is the same as the aforementioned method by (Ahmad et al., 2018), but in this research, it was implemented in a static and multi-hop data transmission environment because of the fast-searching feature of the algorithm. The fitness function is based on residual energy and node degree, used by the bee colony algorithm to select the CH efficiently. PBC-CP performed well in terms of extending network lifetime compared to several existing protocols.

Lavanya and Shanker got inspired by the energetic searching and gliding behaviour of flying squirrels and proposed a CH selection method using a squirrel search algorithm (SSA) in a homogeneous network (Lavanya & Thangavelu, 2020). In this literature, the energy of nodes acts as the food source while the squirrel movement is the changing location of the CH. The authors also introduced seasonal monitoring conditions, gliding constant, and predator presence probability to avoid the algorithm from falling into local optima and to give a balance between the exploration and exploitation capability. The CHs are selected based on a fitness function that considers energy and distance. From the simulations, even though the first node had died quicker in SSA as compared to other metaheuristic algorithms, it was found to perform better at the end, than any other algorithms, and helped in extending the network lifetime.

2.4.2 Modified/Extended

The authors in (Li et al., 2017) proposed a multi-objective clustering and routing method in WSNs by using an improved non-dominated sorting particle swarm optimizer (INSPSO). When we say multiple objectives, it means there is the inclusion of minimizing and maximizing objectives, whereas in this paper, the sum of residual energy must be maximized, and the energy consumption must be minimized to select the optimal CH. The performance evaluation is done by considering heterogeneous scenarios where the network has different numbers of sensors and gateways. INSPSO efficiently selected the CH through multi-objective factors by improving the network lifetime and reducing energy consumption.

Since the usage of the swarm intelligence algorithm shows many improvements in CH selection, Sarkar and Murugan proposed a CH selection and routing method based on firefly with cyclic randomization (FCR) in a single hop environment (Sarkar & Senthil Murugan, 2017). Compared to (D. Prasad et al., 2017), FCR replaces the firefly by following certain conditions in a particular cycle, and FCR can also handle multiple objectives. The CHs are selected based on a cost function that includes distance, energy, and delay as parameters. Simulation results show that FCR performs better than some existing algorithms.

Metaheuristic algorithms are not only used to achieve energy efficiency but they are also used for optimized area coverage, as discussed by Peng and Xiong in (Peng & Xiong, 2019). In this literature, improved adaptive PSO (IAPSO) is applied to solve coverage and energy optimization problems in a single-hop environment, where the inertia weight in PSO is adaptively changed for balance exploration and exploitation capability. To optimize the energy consumption problem, an optimal CH is selected based on CH candidates' total residual energy ratio and energy consumption balance degree. Comparison with some existing algorithms shows that IAPSO performs well in terms of achieving balanced energy consumption.

Mood and Javidi, on the other hand, proposed a modified gravitational search algorithm (GSA) in WSNs (Ebrahimi.M & Javidi, 2019). Since it is very important to have a balance between exploitation and exploration, GSA is modified with varying mass values over time and the inclusion of a tournament selection method. Modified GSA uses a fitness function based on the distance of nodes to the CH and residual energy to select the optimal CH. The proposed method was evaluated using several unimodal functions, basic multimodal functions, and composition functions, where modified GSA performed well in terms of network lifetime and delivery of data packets.

Table 2.4: Comparison of conventional and modified/extended version of non-hybrid metaheuristic method used in WSN

Method (Author)	**Objective(s)**	**Selection Criteria (Objective Function)**	**Advantages**	**Limitations**
		Conventional		
EPSO-CEO (Vimalarani et al., 2016)	Maximizing the lifetime.	Average distance and average energy of the member nodes	Routing and data aggregation by CH is discussed by calculating the cost path for efficient routing.	Usage of PSO may lead to be trapped in local optima.
ABC (Mann & Singh, 2016)	Minimum energy consumption. Least hop-count for data packet delivery.	Energy, the distance between CH and BS	Uses TDMA schedule to ensure that there will be no collisions among data packets sent by various nodes.	ABC has drawbacks like preference on exploration at the cost of exploitation and skipping the true solution due to large step sizes.
FFCHSA (D. Prasad et al., 2017)	Minimize energy consumption.	End-to-end delay, packet delivery ratio and energy consumption.	The algorithm helps to avoid selecting multiple CH nodes to reduce complexity and unnecessary energy consumption.	Firefly algorithm usually suffers from the drawback of easily getting stuck at local optima.
WOA-C (Jadhav & Thangavelu, 2017)	Maximizing the energy efficiency of the network.	Residual energy of the node and the sum of energy of adjacent nodes.	WOA has some sort of balance between exploration and exploitation capability. TDMA (Time Division Multiple Access) and CDMA (Carrier Sense Multiple Access) is used to avoid collision of data.	The fitness function only focuses more on the exploration capability of the algorithm.
CSO (Q. X. Wang & Zhu, 2017)	Reduce the energy consumption of the WSN. Improve the survival time of the network.	Energy consumption, the distance between CH and BS and cluster compactness	Levy flight is used to make CSO jump out of local optima and to ensure global capability.	CSO will be trapped into local optimum.

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Table 2.4, continued

Method (Author)	Objective(s)	Selection Criteria (Objective Function)	Advantages	Limitations
BeeWSN (Ahmad et al., 2018)	Minimize the end-to-end delay.	The remaining energy of node, degree, speed, and direction	The search process is designed in such a way that both the exploitation and the exploration of honeybees can be carried out jointly.	HBA may skip the true solution due to large step sizes (Fall into local optimum).
SSO (H. A. Shehadeh et al., 2018)	Minimize end-to-end delay and end-to-end latency. Maximize energy efficiency and network throughput	N/A	The algorithm considers fast-paced sperms, which shows that the algorithm has better exploitation capability.	SSO has similar features as PSO, which means the method will be trapped in a local optimum.
SSMOECHS (J. G. Lee et al., 2019)	Extend the lifetime and stability.	Node distribution, node energy, distance	The optimal CHs are obtained from sampling and optimized using a modified SMO algorithm, thus preventing the divergence between the ideal CH location and the actual CH node location.	In SMO, if nodes are with discrete locations, they will fail the exploration. The weight must be appropriately set to be used as the sampling probability, or the expected value will be wrong.
EWA (Pasupuleti & Balaswamy, 2019)	Minimize the energy consumption. Minimize the delay.	Energy, distance, and delay	Discusses the hotspot problem. Usage of Cauchy mutation operator to make EWA jump out of local optima. Optimal route selection is also made.	EWA may fall into local optima.
GA (Nayak et al., 2019)	Optimize energy consumption.	Highest residual energy and lowest distance to BS	Discusses hotspot/energy hole problem.	GA can be slow in terms of convergence. It can also be inaccurate.

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Table 2.4, continued

Method (Author)	**Objective(s)**	**Selection Criteria (Objective Function)**	**Advantages**	**Limitations**
PBC-CP (Pathak, 2020)	Prolonging network lifetime.	Node's energy, degree of node, and distance from base station to node	The search process is designed in such a way that both the exploitation and the exploration of honeybees can be carried out jointly. Uses TDMA to avoid packet collision.	ABC is well known for drawbacks like preference on exploration at the cost of exploitation and skipping the true solution due to large step sizes.
SSA (Lavanya & Thangavelu, 2020)	Maximize energy efficiency.	Sensor nodes energy and distance between the interactive elements	Discusses trade-offs between exploration-exploitation and global search constraints.	Focuses on saving energy when the network is low on energy (Seasonal monitoring condition). PSO performs better than SSO when fewer rounds are applied.
		Modified/Extended		
INSPSO (Li et al., 2017)	Equilibrium between total energy consumption and energy balance.	Residual energy and distance	The hot spot problem is discussed by using passive and active ways to determine the residual energy of nearby nodes.	Gateways/CHs are predefined, where the cost overhead involved in planning the network can be increased.
FCR (Sarkar & Senthil Murugan, 2017)	Maximize the energy efficiency. Minimize time delay.	Energy, distance, and delay	Usage of cyclic randomization improve the performance of the algorithm. Discusses the ability of FCR to handle multiple objectives.	Firefly algorithm will easily get stuck at local optima. The proposed algorithm suffers a high computational cost, which requires substantial minimization. High processing complexity.

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Table 2.4, continued

Method (Author)	Objective(s)	Selection Criteria (Objective Function)	Advantages	Limitations
IAPSO (Peng & Xiong, 2019)	High coverage ratio. Low redundancy ratio. Energy consumption balance.	Residual energy ratio and energy	Discusses multi-objective optimization model due to the uncertainty between coverage ratio and redundancy ratio. To achieve better optimization, this paper improves inertia weight to PSO.	PSO individually may fall into local optima. The number of cluster heads influences the number of nodes alive using IAPSO, which will not be efficient.
MO-GSA (Ebrahimi.M & Javidi, 2019)	Maximize the WSN's lifetime. Maximize energy efficiency.	Distance of nodes to their corresponding cluster head and remaining energy	Focuses on controlling exploitation and exploration capabilities of GSA by using Tournament selection. TDMA schedule is organized by the cluster head to avoid data collisions.	Solely focuses on energy efficiency and does not consider QoS. GSA will have problems with exploration and exploitation if treated separately.

2.5 Hybrid Metaheuristic Algorithms in WSN

Mobile ad-hoc networks (MANETs) are known to self-organize mobile devices that are autonomous and can move freely, making them an infrastructure-less wireless network (M. Kumar & Mishra, 2012). In the year 2019, Prasad and Balakrishna proposed an improved genetic algorithm with simulated annealing (SAGA) to improve network lifetime and energy efficiency in MANETs (A. Y. Prasad & Rayanki, 2019). The CH in this literature is selected based on the CH degree and the energy value. The genetic algorithm has greater global search capability but has problems such as slow convergence rate and weak local search capability. The authors claimed that SAGA would be able to overcome genetic algorithm limitations and large combinational optimization problems in MANETs. From the simulations, the SAGA protocol was able to select CHs with better performance compared to other existing protocols.

In 2016 (R. Kumar & Kumar, 2016) proposed a new hybrid ABCACO algorithm which consists of the artificial bee colony (ABC) algorithm and the ant colony optimization (ACO) algorithm. The ant colony algorithm is based on ants' food-hunting behaviour, which uses pheromone trails to communicate which each other. This paper focuses on tackling the squared optimization problem by dividing the field into subregions where ABC is used for CH selection, and ACO is used to get optimized routing in a multi-hop WSN environment. The CH selection process is achieved using a fitness function containing parameters such as communication energy and the distance from nodes to the BS. A sub-cluster head (SCH) is also selected using the fitness function in each subregion part to communicate with nodes and the CH. The authors also discussed the use of the proposed scheme in real-time fire detection applications. ABCACO managed to decrease the communication distance and increase network lifetime, stability and goodput compared to a few existing algorithms.

A hybrid harmony search algorithm (HSA) and PSO (HSA-PSO) were proposed in (Shankar et al., 2016) for energy-efficient CH selection in WSNs. HSA is based on the concept of finding the pleasing harmony by a musician, and HSA is deemed to have good exploration capability (Askarzadeh & Rashedi, 2017). The proposed algorithm gives a balance between global search and local search to obtain the optimal CH. The CH is selected based on Euclidean distance f_1 and the ratio of initial energy of nodes f_2, where the objective functions f_{obj} are calculated with the inclusion of scaling factor ε, as shown below:

$$f_{obj} = \varepsilon * f_1 + (1 - \varepsilon) * f_2 \tag{2.5}$$

The proposed algorithm managed to have a higher searching capability in high dimensional problems and outperformed the non-hybridized algorithm in terms of network lifetime and throughput.

In recent years of research, a multi-weighted chicken swarm-based genetic algorithm (MWCSGA) for energy-efficient clustering in multi-hop WSNs was proposed in (Ajmi et al., 2021). The GA's crossover and mutation operators are embedded into the Chicken Swarm Optimization (CSO) algorithm to ensure diversity in obtaining the optimal solution. The efficient CH is selected by considering the energy consumption, distance between CH and BS, and distance between node and CH in fitness function evaluation. The multi weights in terms of localization of nodes and their residual energy are also added before selecting the CH, to reduce energy consumption. From the simulations, it was evaluated that MWCSGA performed better as compared to several existing state-of-the-art methods in terms of energy efficiency, end-to-end delay, throughput, and packet delivery ratio.

In (Sahoo et al., 2020), the authors proposed a hybrid approach to optimize clustering in WSNs. The hybrid approach considers genetic algorithm (GA) and particle swarm optimization (PSO), termed as (GAPSO-H), where GA is used to select the optimal CH and PSO is used to select optimal routing for the mobile sink in a heterogeneous network. Three levels of energy heterogeneity are deployed which are super node, advanced node, and normal nodes. The fitness function that is used to select the best CH comprises of five fitness parameters which are residual energy, average energy, the distance between sink and node, number of neighbours, and energy consumption rate. The proposed GAPSO-H outperformed several existing algorithms as it achieved an improved stability period.

In (Rambabu et al., 2019), the authors proposed a hybrid artificial bee colony and monarch butterfly optimization algorithm (HABC-MBOA) for optimal CH selection in WSNs. MBOA is based on the migration of butterflies from one area to another (Ghetas et al., 2015). In this literature, the algorithm is proposed to prevent the solutions from falling into local optimal by replacing the employee bee phase of ABC with a mutated butterfly-adjusted operator. The CH selection is done based on residual energy, the distance between CH and BS, and the inter-cluster distance. The simulation was carried out with a huge number of sensors and varying sink positions and showed that the proposed algorithm outperforms several existing algorithms in terms of the number of nodes alive and the throughput.

Lavanya and Shanker proposed an energy-efficient CH selection algorithm using a hybrid squirrel harmony search algorithm (SHSA) in a homogeneous WSN (Lavanya & Shankar, 2019). The non-hybrid squirrel search algorithm (SSA) was introduced in the year 2020, as discussed in the non-hybrid section. The main objective for the authors to introduce a hybrid method was to have a balance between the exploration and exploitation capability, where SSA, which has a good global search ability and harmony search algorithm (HSA) displays high search efficiency in a search space. The CH is selected based on the fitness function used by SHSA, which contains energy and separation energy as the fitness parameters. The SHSA was found to outperform the non-hybrid version by having an extended first node death, making it extend network lifetime by increasing the energy efficiency.

Another new hybrid metaheuristic algorithm for CH selection proposed by the authors in (Dattatraya & Rao, 2019) is called a new fitness-based glowworm swarm with fruitfly algorithm (FGF), which hybridizes glowworm swarm optimization (GSO) and fruitfly optimization algorithm (FFOA). The concept of GSO is based on a luminescence amount called luciferin of glowworm to determine its movement and its neighbours (Thiruvenkadam et al., 2017), whereas FFOA is based on the concept of the food-searching behaviour of fruit flies. GSO and FFOA have some limitations such as poor local search capability and less convergence rate, respectively. To perform effective CH selection, the algorithms are hybridized to solve the problems above and certain parameters such as distance, delay, and energy utilized are used in fitness calculation. The comparison of FGF with some hybrid and non-hybrid algorithms showed that FGF performed better in terms of nodes being alive and energy consumption.

LEACH-C (W. B. Heinzelman et al., 2002) was proposed earlier, and uses the simulated annealing algorithm in CH selection, which causes more computation process time and consumes more energy. To overcome this issue, the authors in (Pitchaimanickam & Murugaboopathi, 2020) proposed a hybrid approach of the firefly algorithm with particle swarm optimization (HFAPSO). HFAPSO is embedded in LEACH-C to obtain optimal CHs to improve network lifetime, where the fitness function is evaluated using the remaining energy of the nodes and the distance between nodes and the CH. HFAPSO in the LEACH-C algorithm managed to prolong network lifetime and reduce energy consumption compared to the firefly algorithm and conventional LEACH-C algorithm.

In the year 2021, another hybrid algorithm consisting of the GWO algorithm and Sunflower Optimization (SFO) termed HGWOSFO was introduced (Lavanya & Shankar, 2021). In this literature, the authors ensure exploration and exploitation based on the algorithms used where SFO is used for exploration, where SFO is basically the idea of sunflowers growing towards the sun, and GWO is used for the exploitation process. The CH selection process in this work focuses on objectives that are energy and distant constraints. The algorithm's results are then compared to some existing non-hybrid algorithms and show better performance in network lifetime. However, the results will not yield a good justification on its performance as it compares with algorithms that are not hybridized for exploration and exploitation capabilities.

Table 2.5: Comparison of hybrid metaheuristic method used in WSN

Method (Author)	**Objective(s)**	**Selection Criteria (Objective Function)**	**Advantages**	**Limitations**
SAGA ((A. Y. Prasad & Rayanki, 2019)	Improve network lifetime. Minimize energy consumption.	Residual energy and distance	Fusion of GA and SA algorithm is implemented to overcome the large combinational optimization problems.	SAGA has a higher routing overhead with a greater number of nodes. It is more towards exploration capability and no discussion on the balance between exploration and exploitation capability.
ABCACO (R. Kumar & Kumar, 2016)	Improved network stability. Increase the Network lifetime.	Energy and distance	Discusses square optimization problems and scalability. Discusses the application of fire detection in real-time.	Usage of 2 algorithms separately will increase the overall method complexity.
HSA-PSO (Shankar et al., 2016)	Improve energy consumption. Improve network lifetime.	Residual energy and distance	The proposed hybrid approach uses the high searching efficiency of HSA combined with the dynamic nature of PSO. It focuses on exploration and exploitation balance in the algorithm.	PSO faces high dimensional optimization limitations, and HSA is restricted to only a certain region when they are treated separately.
MWCSGA (Ajmi et al., 2021)	Reduce energy consumption. Increase the lifetime of the network.	Energy consumption, the distance between the CH and the BS, and the distance between nodes and the CH.	Selects the second CH for fault tolerance. The CH selection is enhanced by using the genetic algorithm crossover and mutation process to maximize the diversity of the network population. Multi weight model that works with uniform clustering is used to ensure a reduction in energy consumption	The algorithm contains six sections which will increase the complexity of the overall algorithm. GA has a slow convergence by nature. There is a possibility of experiencing delays during communication.

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Table 2.5, continued

Method (Author)	**Objective(s)**	**Selection Criteria (Objective Function)**	**Advantages**	**Limitations**
GAPSO-H (Sahoo et al., 2020)	Improve energy consumption and network lifetime.	Energy, distance, node degree, average energy, and Energy Consumption Rate (ECR).	GAPSO-H addresses the hot-spot problem. GAPSO-H is found to be computationally optimized. Focuses on a balance between global and local searches.	Using nodes with different energy levels can increase the process complexity. Mobility of the sink can be expensive.
HABC-MBOA (Rambabu et al., 2019)	Improve energy consumption and network lifetime.	Residual energy, the distance between the cluster head, the base station and inter-cluster distance extracted from the network.	Focuses on escaping the local minima and delayed convergence problem. Focuses on a balance between exploration and exploitation. The spectral clustering method is used by the base station to construct the graph modelling for optimized clustering. Levy flight or mutation operators are used for diversity.	Both conventional Monarch The butterfly Optimization Algorithm and Artificial Bee Colony algorithm suffer from falling into local optima problems when treated separately.
SHSA (Lavanya & Shankar, 2019)	Improve the overall throughput and residual energy of nodes.	Energy and separation energy	Focuses on the exploration and exploitation capability to select the optimal CH.	The hybridization of two algorithms will increase the overall complexity.

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Table 2.5, continued

Method (Author)	Objective(s)	Selection Criteria (Objective Function)	Advantages	Limitations
FGF (Dattatraya & Rao, 2019)	Maximize the network's lifetime and energy efficiency. Minimize delay.	Energy, the distance among nodes, packet delay	Focuses on achieving a good exploration and exploitation capability. This proposed work also considers the QoS parameter as the major parameter for efficient network performance.	GSO suffers in solving the high dimensional problem and has poor local search capability, whereas FFOA has less convergence rate in search space when treated separately. The proposed method does not perform efficiently with fewer rounds in terms of nodes alive.
HFAPSO (Pitchaimanickam & Murugaboopathi, 2020)	Minimize the energy consumption.	Energy and average distance	HFAPSO tries hard to mutually balance the trade-off between computational cost and network lifetime. The computational cost of the developed HFAPSO is inexpensive.	The time complexity of the proposed algorithm will be increased compared to the non-hybrid algorithms. Both Firefly and PSO will fall into local optima.
HGWOSFO (Lavanya & Shankar, 2021)	Prolong network lifetime	Energy and distance	HGWOSFO tends to balance out the exploration and exploitation based on its conventional algorithms. It also has lower time complexity of $O(n)$.	The justification of the performance is not appropriate as it is compared with non-hybrid methods.

2.6 Metaheuristic Algorithms on Test Function Optimization and Other Fields

Metaheuristic methods are not only used in WSN but also in different fields such as engineering (Kaveh, 2017), robotics (Cruz-Bernal, 2013) and finance (Soler-Dominguez et al., 2017). So, in this section, the metaheuristic, which is non-hybrid and hybrid, used to optimize the test functions and used in other fields are discussed in detail. Most of the researchers used test functions from "Congress on Evolutionary Computation (CEC)" CEC 2013, CEC 2015 and CEC 2017 benchmark test functions. CEC is a well-known conference by the IEEE Xplore Digital Library where many optimization methods and test functions that cover evolutionary computations are presented.

2.6.1 Non-Hybrid

Testing an algorithm with good benchmark functions enables us to ensure the performance of an algorithm in different scenarios. As such, a modified GA with a three-parent crossover was proposed to solve the CEC' 2013 competition problems on real-parameter optimization (Elsayed et al., 2013). The authors consider a crossover using three parents compared to the conventional two-parent crossover in the idea of making two parents facilitate exploitation and one parent facilitate exploration. A new diversity operator was also introduced to ensure the algorithms do not prematurely converge. The proposed algorithm is evaluated under five unimodal problems, 15 multimodal problems and eight composite functions. The algorithms are also run under various dimensions varying from 10, 30 and 50 for quality evaluation. However, the paper does not compare the results with its state-of-the-art, which is a disadvantage to claim its performance strength.

In the year 2015, the close competitor of GA, the PSO algorithm, was proposed to optimize CEC' 2015 Competition on single objective multi-niche optimization (Cheng et al., 2015). In this paper, the author tests seven variants of PSO, which are PSO with star structure, PSO with ring structure, PSO with four clusters structure, PSO with Von Neumann structure, social-only PSO with star structure, social-only PSO with ring structure, and cognition-only PSO. The seven variants of PSO are tested on 8 CEC's expanded scalable functions and seven composite functions. The results show that the PSO with ring structure outperforms the other PSO variant. Similarly, to (Elsayed et al., 2013), the paper lacks the comparison of the proposed variants with different algorithms to claim its performance success.

In recent years, a new comprehensive learning gravitational search algorithm (CLGSA) was proposed based on GSA, which ensures a better ability to choose good elements (Bala & Yadav, 2020). The authors in this paper discuss that the comprehensive learning strategy proposed will enhance the limitation of GSA, which is the algorithm being trapped in local optima and slow convergence. The proposed method was evaluated with 28 benchmark test functions from CEC' 2013 benchmark suite. The results are compared with eight other existing algorithms. From the comparison, CLGSA delivers stable results with a good converging ability and statistical significance.

The emergence of new algorithms from many inspirations has inspired some researchers to propose a new metaheuristic algorithm called Honey Badger Algorithm (HBA) (Hashim et al., 2022). HBA is developed based on the concept of honey badger foraging, which is developed to have an efficient search strategy. The dynamic search behaviour with digging and honey finding of the honey badger unlocks the exploration and exploitation capability of the algorithm. The author also mentioned the randomization technique, which ensures the diversity of the population for efficient searching. The proposed method was evaluated in 30 benchmark test functions from CEC' 2017 test suite and four engineering design problems. The results show that HBA is superior to some existing algorithms in terms of convergence speed and balances the exploration and exploitation ability.

2.6.2 Hybrid

The fast convergence nature of PSO and the good global searching ability of GA inspired (Aydilek, 2018) to propose a hybrid particle swarm optimization and genetic algorithm (HPSOGA). Since PSO is usually easily trapped in local optimum, the author integrated the genetic operator of GA, which consists of crossovers and mutations, into PSO, which promotes a good balance between exploration and exploitation capabilities. The proposed algorithm was evaluated and tested with engineering-constrained optimization problems such as pressure vessel design and welded beam design. The results showed that the proposed method is more effective and robust compared to the conventional GA and PSO algorithms.

A very good example of the hybrid method is the hybrid firefly and particle swarm optimization (HFPSO) algorithm which was introduced by (Aydilek, 2018) and is used to obtain global solutions for computationally expensive numerical problems. The author's motive was to combine the strengths of both algorithms in obtaining a method with a balance of exploration and exploitation capabilities. In this paper, the author uses PSO for global searching as it is deemed to have fast convergence and FA for local searching as it fine-tunes the exploitation. The developed hybrid method was then evaluated using CEC 2015 and CEC 2017 benchmark functions consisting of unimodal, simple multimodal, hybrid, and composition functions. The results showed that the proposed HFPSO method performs much better than standard PSO, FA and other hybrid methods. The disadvantage of this hybrid method is that it will not have the best balance between exploration and exploitation, as swarm-based algorithms are known for better exploitation as opposed to exploration.

The overwhelming use of hybrid algorithms inspired (Şenel et al., 2019) to propose a new hybrid particle swarm optimization and grey wolf optimization (HPSOGWO) algorithm to obtain global solutions by having balanced exploration and exploitation capabilities. The authors stated that the GWO algorithm reduces the possibility of PSO falling into the local minimum. The developed hybrid method was evaluated on five benchmark functions and three real-world problems that consisted of parameter estimation for frequency-modulated sound waves, process flow sheeting problem, and leather nesting problem (LNP). The results showed that HPSOGWO performs better than the standard PSO, GWO, ABC, SSA, and three hybrid PSO–GWO approaches in terms of converging to lower-cost values with fewer iterations. However, the time complexity of HPSOGWO is higher than standard PSO and GWO, but the authors' concern was getting higher performance.

In recent research, (H. Shehadeh, 2021) proposed a hybrid sperm swarm optimization and gravitational search algorithm (HSSOGSA) to ensure a good balance between exploration and exploitation capabilities for global optimization. SSO seemed to outperform the well-known PSO in obtaining global solutions, which motivated the author to combine the capability of exploitation in SSO with the capability of exploration in GSA. This combination of SSO and GSA was done using a co-evolutionary heterogeneous low-level hybrid technique, as both approaches run simultaneously, reducing the method's time complexity. To evaluate the efficiency and performance of the proposed method, the author tested HSSOGSA under different testbed problems of optimization called the CEC 2017 suite. The results described that the proposed method has greater performance in jumping out of local extremes with a faster rate of convergence compared to the standard SSO and GSA methods in most of the CEC 2017 suite benchmark functions.

Since certain algorithms contribute hugely to a good balance between exploration and exploitation, (H. A. Shehadeh et al., 2022) recently proposed a Hybrid Genetic Algorithm and Sperm Swarm Optimization (HGASSO) to optimize multimodal functions. The authors applied local search, which is SSO first to select the global best solution and personal best solution before the selection, crossover and mutation are applied to jump out of the local minima easily. The method was tested with 11 multimodal minimization test functions, and it is compared with the conventional SSO and GA. From the results, the proposed hybrid method outperformed the conventional methods in 6 out of 11 test functions, performed the same with SSO in 2 out of 11 test functions and performed equally to the conventional methods in 3 out of 11 test functions. The authors also used One-way ANOVA (Tukey's test) to determine the significance of the results to justify the performance of the proposed method. Even though the results seem convincing, the authors did not ensure the performance of the method in unimodal optimizations, as some hybrid algorithms will not perform well in unimodal functions. Moreover, the comparison between existing hybrid algorithms limits the justification of the algorithm's performance.

2.7 Adaptive Parameter Tuning Metaheuristic Algorithms

The advancement of metaheuristics has helped and enhanced the results in many fields. As such, researchers are keen to investigate further on the metaheuristic algorithms to obtain even more efficient solutions. This has led to research based on parameter tuning as early as 2006. In the article ((Iwasaki et al., 2006), the authors proposed an adaptive parameter tuning to PSO. In PSO, the velocity of the particles is focused because higher velocity makes the algorithm explore, and lower velocity makes the particles immobile and contributes to exploitation. The authors in this paper proposed to adjust the parameters below adaptively:

$$\begin{aligned} &If\ v_{ave}^{(k+1)} > v_{ideal}^{(k+1)}, then\ set\ w^{(k+1)} = max(w^k - \triangle w, w_{min}) \\ &If\ v_{ave}^{(k+1)} < v_{ideal}^{(k+1)}, then\ set\ w^{(k+1)} = min(w^k + \triangle w, w_{max}) \end{aligned} \tag{2.6}$$

So, this shows that when the average velocity, v_{ave} of the particles is higher than the ideal velocity, v_{ideal}, the parameters, such as inertia weight w, will be shifted towards convergent values while the if the v_{ave} of the particles are higher than the, v_{ideal}, the parameters w, will be shifted towards divergent values. The proposed method is compared with the existing Linearly Decreasing Inertia Weight Approach (LDIWA). The results show that the proposed algorithm has higher optimality than LDIWA.

Not only PSO but also GA has attracted many researchers to explore its parameter tuning to improve the algorithm. (Dong & Wu, 2009), the authors' motive was to boost the convergence rate and to ensure GA to jump out of the local optimum easily. So, they proposed an adaptive crossover and mutation based on expansion sampling. In this article, the crossover probability, Pc, is adjusted based on the following equation:

$$Pc = \frac{|f(a) - f(b)|}{max(f) - min(f)} \tag{2.7}$$

Where $f(a)$ and $f(b)$ are the fitness of two selected chromosomes while $max(f)$ and $min(f)$ are, respectively, the largest and the smallest fitness in the population. This adaptive crossover rate ensures that individuals from both ends of the population are crossover as it will reduce the intense competition in making a choice for the next round. On the other hand, the article discusses the mutation probability, Pm, as follows:

$$Pm = k * (\frac{f(a)}{max(f)})^2 \quad 0 < k < 1 \tag{2.8}$$

Where $f(a)$ is the fitness of the individual and $max(f)$ is the largest fitness in the population. This mutation rate ensures that the better individuals do not occupy the entire population quickly to avoid the algorithm from falling into the local optimum. Two experiments were conducted to test the performance of the proposed algorithm with existing modified GA algorithms, where experiment 1 is based on a complex optimization function and experiment 2 is based on the needle in a haystack problem. The results show that the proposed algorithm has outperformed the others.

In recent years, parameter-tuning processes have been applied to metaheuristic algorithms such as GSA. The fixed constant in GSA contributes to the gravitational constant (G), which behaves as the monotonic decreasing function, which leads to more exploitation that results in rapid loss of diversity and premature convergence. To solve this issue, the authors in (Joshi & Bansal, 2020) proposed a generalized strategy to find the most suitable value of constant . To do that, the strategy uses elementary effect matrix (EE) as elementary weight matrix (EW) to obtain the most suitable value as required by the search. Next, the optimal value of for G will ensure the diversity of the search mechanism is preserved. To ensure the superiority of the proposed variant of GSA, the performance is compared to some recent variants of GSA and some state-of-the-art algorithms by evaluating on CEC 2015 test suite. The results show that the proposed method shows an excellent search ability compared to the others. The proposed strategy is also remarked to be used to tune other algorithms also, but it may increase the overall time consumed if it is implemented in real-life large-scale optimizations.

This literature and research work shows that there is potential for any algorithms to be enhanced and improvised by having adaptive parameter tuning, which is one of the motivations for this paper to include adaptiveness in our proposed method.

2.8 Other existing methods in WSN

When it comes to WSN, many other methods of routing and environments exist to ensure the performance of network lifetime and data delivery are at their highest. For example, in the year 2016, the authors of (Akbar et al., 2016) proposed a method with four variants, namely, balanced energy-efficient network-integrated super heterogeneous (BEENISH), improved BEENISH (iBEENISH), mobile BEENISH (MBEENISH), and improved mobile BEENISH (iMBEENISH) protocols. The research was carried out on heterogeneous nodes in two different environmental settings, with sink mobility and without sink mobility. Moreover, the mobile sink technique is adapted and deployed using the starfish routing by authors of (Habib et al., 2016, 2020). Starfish routing enables the WSN network nodes to communicate with other nodes independently using the backbone of a starfish design. It was proven that this routing method outperformed some existing methods in terms of lifetime and data delivery delay. Besides, the author in (Hu et al., 2018) proposed rendezvous node selection for a mobile sink scenario. The rendezvous node acts similarly to a CH, storing information from other nodes for the mobile sink to be collected later. The proposed method reduced energy consumption and increased the network lifetime compared to several existing algorithms. However, a mobile sink which frequently updates its position can cause more energy consumption and higher collisions in the network (Yarinezhad, 2019). Using starfish routing as well promotes individual routing needs more effort and planning as the network grows into a more extensive network. The clustering process in WSN is still a vital research topic as it allows improved reliability and efficient connectivity (Shahraki et al., 2020).

2.9 Chapter Summary

This chapter has discussed clustering and its advancement in the field of WSN in depth, where LEACH was a significant finding to mitigate the sensor nodes' limitations. The isolated node and hotspot problem is vital in clustering, which requires a proper CH selection mechanism. Having selection criteria for CH selection can be troublesome as it needs a strong assumption with high calculation time. So, the metaheuristic method allows efficient CH selection and cluster formation given that it overcomes two major problems: being trapped in local optima and having a slow convergence rate. If these issues are not resolved, appropriate CH will not be selected, contributing to the initially isolated node and hotspot problems. To ensure these significant problems of metaheuristic methods are mitigated, a metaheuristic method with well-balanced exploration and exploitation capabilities should be investigated. The literature review shows that this is achievable by hybridizing two distinct algorithms. The existing metaheuristic methods show that it has great potential in many other fields, which confirms that using the metaheuristic method in WSN will ensure the mitigation of WSN problems. Moreover, the literature review also depicts that tuning the parameters of a metaheuristic method based on environmental changes allows for better performance. As such, adaptiveness in selecting CH and forming clusters should be studied. WSN needs certain objectives to select the optimal CH, as these objectives will be fed into the metaheuristic methods. So, having a refined objective function will enable better CH selection, ensuring good network stability and inter-cluster communications.

CHAPTER 3: METHODOLOGY

3.1 Introduction

The research methodology outlines the methods used in our research, which involve the learning of techniques that will help in the conduct of the research (Goundar, 2012). The methodology used in this research is based on a sequential approach, and it is in line with achieving the objectives of this research. In this research, there are 4 phases that exist to ensure that every aspect of the research is covered, as illustrated in Figure 3.1.

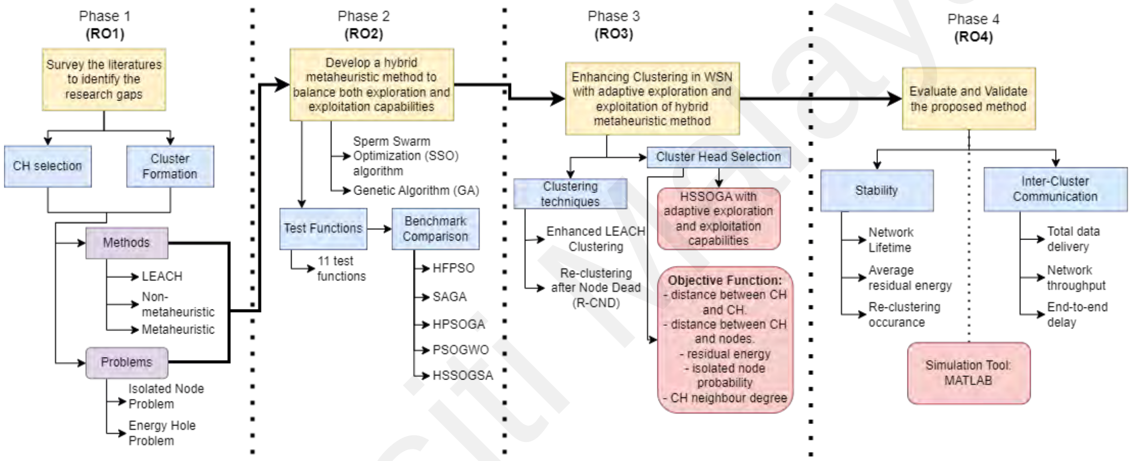

Figure 3.1: Phases of Research Design

This chapter is organised as follows, where section 3.2 states the steps and work of phase 1 to phase 4 of the methodology in detail. In section 3.3, a clear mapping between the research objectives and the methods utilised is summarised. Finally, section 3.7 includes an overall summary of this chapter.

3.2 The Phases of this research

In phase 1, the literature is surveyed and reviewed to identify the research gaps in the clustering of WSN, where the intervention of various methods in CH selection and cluster formation are reviewed as in Chapter 2. Upon finding the research gaps, a hybrid metaheuristic method is developed to ensure the balance between exploration and exploitation capabilities to perform well in obtaining global solutions in unimodal and multimodal test functions. However, this only helps to ensure that the proposed hybrid method has a good base for real-life scenarios. So, in phase 3, the proposed method is enhanced with adaptive exploration and exploitation capabilities to ensure clustering in WSN is enhanced in terms of performance. In phase 4, the performance is analysed and discussed for a better understanding of the performance of the proposed method in WSN. Phase 1 is explained and outlined clearly in the previous Chapter 2, which identifies the gaps in the existing literature. Phases 2, 3 and 4 are outlined in Chapter 4, Chapter 5, and Chapter 6, respectively.

A detailed methodology of the research is depicted in Figure 3.2 below.

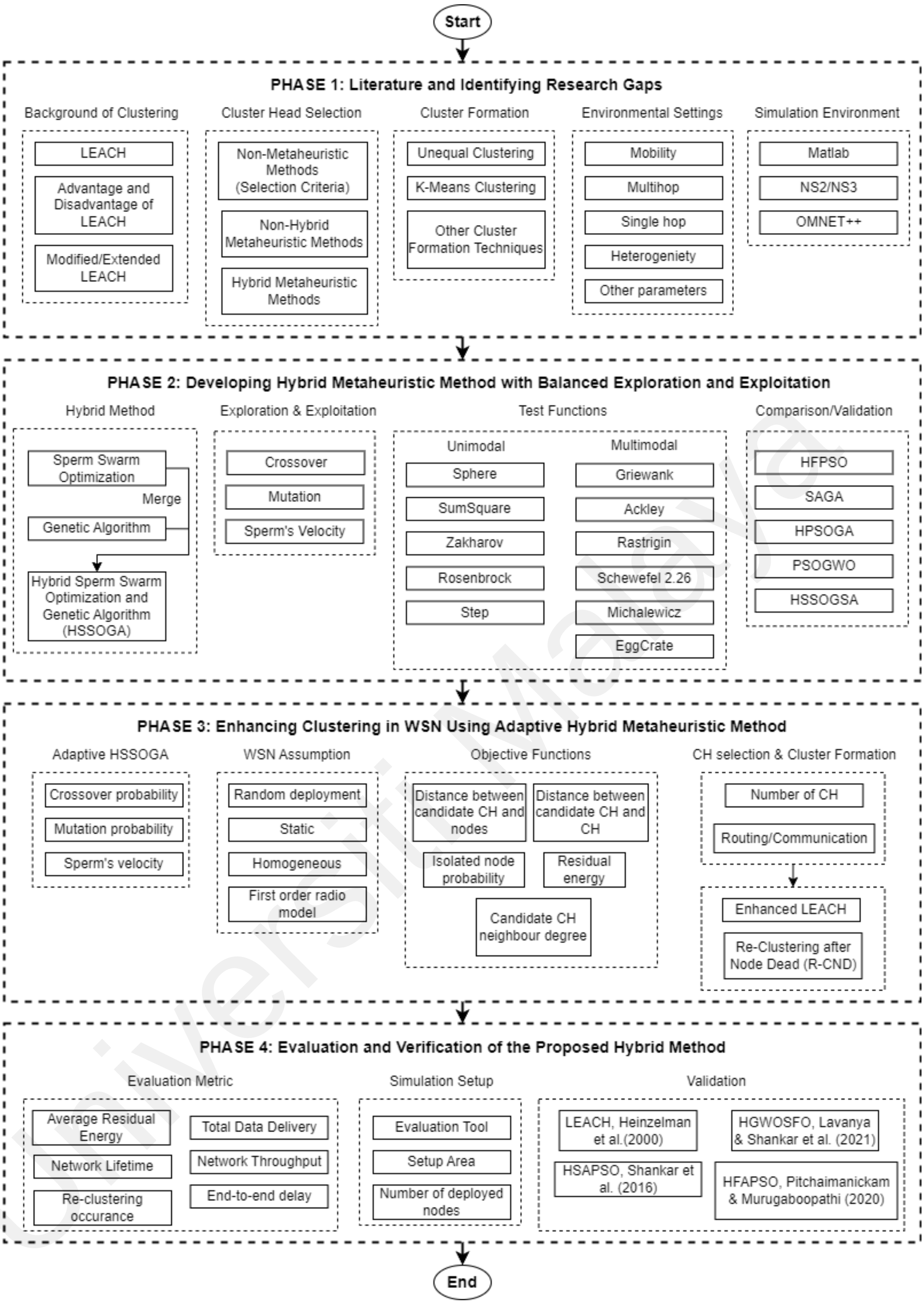

Figure 3.2: Detailed Methodology of the Research

3.2.1 Phase 1: Identifying the Research Gap

The steps in this phase are described in detail in Chapter 2 and briefly outlined below:

1. Initially, the background of clustering is studied and surveyed. The initial clustering method called LEACH (W. R. Heinzelman et al., 2000) is explored in depth as it is said to be the heart of clustering in WSN. The advantages and disadvantages of early clustering are also studied to discover the research gaps and limitations of the method. The existence of limitations on LEACH produced many modified and extended versions of LEACH to enhance the conventional LEACH method for better WSN clustering. These methods are also studied to get an idea of the enhancement and improvisation needed as well as the existing disadvantages possessed by a particular method.
2. Clustering involves two phases which are CH selection and cluster formation phases. Literature that includes methods to select optimal CH is reviewed and surveyed. The CH selection methods are categorised into non-metaheuristic, non-hybrid, and hybrid metaheuristic methods in WSN. The advantages and disadvantages of the methods are outlined to extract the limitations and to define the research gaps. The limitations consist of hotspot/energy hole problems and isolated node problems in WSN, where some existing methods are poorly addressed.
3. On the other hand, literature that includes optimal cluster formation techniques are also surveyed for a better understanding of the joining of member nodes to the CH. The cluster formation techniques commonly used are unequal clustering and K-means clustering, focusing on reducing the energy consumption of the WSN system.
4. The literature is also surveyed and categorised into a few environmental settings of WSN, such as mobility, multi-hop data transmission, single-hop data transmission, heterogeneity, and other parameters/environments that are not commonly used. This clearly shows the most focused environment and what kind of enhanced method will

suit a defined environment.

5. Information from the articles, such as advantages and disadvantages of the methods, time and space complexity of the methods, initial parameters value, simulation software used, and the selection criteria used to optimise clustering in WSN, are listed for a better understanding towards optimised clustering network.
6. The common problem the authors from the literature try to reduce is the energy consumption of the nodes. Besides, the most common objectives used are the distance between CH and nodes, the distance between CH and CH and the residual energy of the nodes.
7. There is also usage of metaheuristic methods for benchmark testing and other applications. These types of articles are surveyed to determine the existence of various hybrid metaheuristic methods in the world compared to the application of WSN. This provides the knowledge on optimizing certain benchmark functions to determine the method's performance.
8. The adaptiveness of a metaheuristic method is also reviewed towards the end of identifying the research gap phase to learn about the importance of a method's parameter values.

3.2.2 Phase 2: Developing the Hybrid Sperm Swarm Optimization and Genetic Algorithm (HSSOGA)

A hybrid algorithm was built based on two distinct metaheuristic methods, which are Sperm Swarm Optimization and Genetic algorithm, to solve 11 unimodal and multimodal test functions from CEC 2017 benchmark suite. The following phase is carried out by the steps outlined below:

1. Initially, a study on existing hybrid algorithms is made to ensure the algorithms which are competitive in the field of optimization. Hybrid Sperm Swarm Optimization and

Gravitational Search Algorithm (HSSOGSA), Hybrid Particle Swarm Optimization and Genetic Algorithm (HPSOGA), hybrid Simulated Annealing and Genetic Algorithm (SAGA), Hybrid Firefly and Particle Swarm Optimization (HFPSO) and hybrid Particle Swarm Optimization and Grey Wolf Optimizer (PSOGWO) are selected in this research.

2. The limitations of these algorithms are extracted, and the proposed hybrid method is compared with these algorithms. This is to ensure that the limitations of an algorithm which are falling into local optima and slow convergence to an optimal value, are compared for the quality of results. The best value obtained over 1000 iterations of an algorithm determines whether the algorithm is stuck in local or global optima. For example, test function Ackley is a multimodal test function with many local optima, but the global optimal value is 0.00 (Surjanovic & Bingham, 2013), the algorithm that yields the best value near 0.00 is deemed to have a better ability to jump out of local optima. On the other hand, the convergence rate is where the algorithms yield a flat curve in obtaining the best value. The quicker the flat curve is formed, the better the convergence rate.
3. Identify the advantages of conventional algorithms of the selected existing hybrid algorithms. Propose a hybrid metaheuristic method based on the advantages to ensure the balanced exploration and exploitation capability of an algorithm is achieved. The proposed algorithm consists of Sperm Swarm Optimization (SSO) and Genetic Algorithm (GA). The GA ensures there are mutation and crossover operators to ensure the sperms of SSO do not converge to local optima. SSO is a phenomenon of sperms moving towards the ovary in the fallopian tube for the fertilization process, which is affected by the temperature and pH values (H. A. Shehadeh et al., 2018).
4. The performance of the proposed method is evaluated based on the following steps:

a) A set of benchmark functions containing unimodal and multimodal test functions will be identified. Moreover, functions with higher dimensions, such as Griewank, are selected to ensure the full potential of the algorithm for optimization. Eleven benchmark test functions such as Sphere, Sum Square, Zakharov, Rosenbrock, Step, Griewank, Ackley, Rastrigin, Schwefel 2.26, Michalewicz and EggCrate are selected to evaluate the performance of the proposed method (Surjanovic & Bingham, 2013).

b) The proposed method is compared with its conventional SSO and GA as well to ensure that hybridizing these algorithms gives an added advantage in performance in terms of best optimal value and convergence rate. The performance of HSSOGA is described in Chapter 4 of this work.

c) The proposed method is also compared with the existing hybrid algorithms identified in 4.(a), proving that the proposed method is competitive to be used in real-world scenarios such as WSN. The significance of performance of the method is determined by using the One-Way ANOVA (Tukey's Test), as depicted in Chapter 4.

3.2.3 Phase 3: Adaptive exploration and exploitation of HSSOGA in clustered WSN

The proposed Hybrid method in phase 2 has been modified to mitigate certain real-life issues of WSN where adaptive exploration and exploitation in terms of adjusting the parameter values are proposed. The following are the steps carried out in phase 3:

1. Identify the literature that is developed to select CH and form clusters in the field of WSN. Literature such as LEACH, Hybrid Firefly Algorithm with Particle Swarm Optimization (HFAPSO), Hybrid Harmony Search Algorithm with Particle Swarm Optimization (HSAPSO) and Hybrid Grey Wolf Optimizer and Sunflower

Optimization (HGWOSFO) are selected to have optimal clustering in WSN.

2. The limitation faced by these studies are outlined, which are energy hole (hotspot) and isolated node issues. Energy hole problems and isolated node problems are deemed to deteriorate the node's energy quicker. Besides, these issues also deteriorate the stability of the WSN network.
3. Modify the proposed method with adaptive exploration and exploitation to control the discovery of the global region and local search to ensure optimal CHs and optimal clusters are formed to mitigate the limitation in 2. The adaptive exploration and exploitation of the metaheuristic method is achieved by the adaptive adjustment of crossover probability, mutation probability and sperm's velocity values to suit the defined WSN environment.
4. The WSN assumption and model consists of the random deployment of nodes which suits the nodes' distribution on environmental monitoring and military monitoring systems. The nodes are deemed to be statically deployed and homogenous. The communications of these nodes are developed based on the first order radio model for energy consumption and data transfer of the nodes to determine the performance of the system.
5. In order to select optimized CH, the proposed method needs to calculate the fitness by using the objective functions that it wants to minimize. The objective functions that are used are the average distance between candidate CH and CH, the average distance between candidate CH and nodes, average residual energy of CHs, maximum CH's neighbour node degree and the average probability of isolated node if the node becomes CH. Proposing probability of the isolated node objective function is to mitigate the isolated node problem. This is to ensure when the clustering process happens, the clusters are formed efficiently considering the nodes that are located

far away from the BS. For example, the objective will adjust the whole clustering of the network to form clusters that cover every node and reduces the excessive energy consumption of far-located nodes. This can be determined by the First Node Death (FND) and Half Node Death (HND) criteria to ensure the proposed algorithm takes longer time for its FND compared to the existing methods.

6. Clustering processes are also enhanced in two forms, namely (1) enhanced LEACH clustering and (2) Re-Clustering after Node Dead (R-CND). For example, the enhanced LEACH clustering method uses a similar technique used in LEACH, but it will only trigger re-clustering if there is a 10% drop in average energy in the network. On the other hand, R-CND will only trigger re-clustering if a node dies off in the network. These techniques are proposed in view of ensuring better network lifetime by reducing the re-clustering occurrence. This is because frequent re-clustering might cause overhead energy consumption that will affect the network's lifetime.
7. The proposed method focuses on selecting an appropriate number of CH that covers the entire network, as well as multi-hop data transmission from CH to CH, is also used to ensure efficient data transfer and limited usage of energy. For example, if a CH is far away from the BS according to the threshold set by the first order radio model, it then finds a shorter distance CH to send its aggregated data to be then transferred to BS. In this way, the energy consumed by CH to transfer data to BS is reduced and the network lifetime is preserved for longer term.
8. The simulation set-up are as follows:
   a) Set the network assumptions and parameters to the standard parameters' settings. For example, the 100 nodes are deployed randomly over a 100m x 100m area. Similar parameters are used for the existing methods for the simulation.
   b) The simulations are run using MATLAB software as much literature uses this

software because of the easy implementation of the environment and precise simulation results based on the review of literature in phase 1.

3.2.4 Phase 4: Evaluation, validation, and discussion of the proposed method in WSN

To ensure the hotspot/energy hole problem and isolated node problems are reduced, the proposed method must be evaluated and validated. The performance of the proposed method is evaluated based on two major criteria which are the stability of the network and inter-cluster communication of the network. So, the evaluation is done with the following steps:

1. Obtain the network lifetime from First Node Death (FND), Half Node Death (HND), Last Node Death (LND), average residual energy and total re-clustering occurrence of the network to ensure the stability of the network. The results are analysed in chapter 6 of this work.
2. Obtain the total data delivery, network throughput and end-to-end delay values to ensure the inter-cluster communication is efficient in the entire network. The proposed method is compared with the existing algorithms with the obtained value to ensure that the network reduces the energy hole and isolated node problem. Further analysis and evaluation are discussed in Chapter 6 of this thesis.
3. he validation of the proposed method is as follows:
    a) The methods mentioned in 3.4.(1.) LEACH, HFAPSO, HSAPSO, and HG-WOSFO are used as state-of-the-art for performance comparison as these literatures show a powerful effect on clustering in WSN.
    b) The proposed method is then compared with the state-of-the-art methods to ensure that network stability and inter-cluster communication is preserved for optimality. For example, in every round, the nodes will use up certain

energy for communication, the network that uses the algorithms to select the CH and form clusters which yields a longer network lifetime, higher residual energy, lower re-clustering frequency, higher total data delivery, higher network throughput and lower end-to-end delay is deemed to have selected best set of CH and forms clusters efficiently. So, the performance metrics consist of average residual energy, network lifetime, total re-clustering occurrence, total data delivery, network throughput and end-to-end delay of the network.

c) Draw comparison graphs of the obtained results for efficient and valid comparison. For example, a graph that shows the longer lifetime of the network till LND has selected better/near-to-optimal CHs and has formed good clusters that reduced the overall energy consumption.

d) Evaluate the results using One-Way ANOVA (Tukey's Test). As it shows the significant performance of the proposed method compared to the other methods, as depicted in Chapter 6.

4. Discuss the superiority of the proposed method in the field of WSN with the analysis of the results as follows.

   a) The space and time complexity of the proposed method is also discussed in Big O notation form to understand the complexity comparison with state-of-art methods.

   b) Outline the advantages and disadvantages of the proposed adaptive metaheuristic method for better analysis of the method.

3.3 Mapping of the objectives and its methodology

Mapping of research questions (RQ), research objectives (RO), brief methodology to obtain said objectives, technique and material used, as well as their expected outcome are outlined below.

Table 3.1: Mapping of RQ, RO, methodology, technique, material and expected outcome.

RQ & RO	Methodology	Technique, Material & Expected outcome
RQ: How to find the research gap that exists in the field of optimization and WSN? RO: To explore the literature on metaheuristic method by understanding its advantages and limitations in the field of optimization and WSN.	Review the literature on methods used in optimizing WSN. The methods surveyed should consist of LEACH (traditional clustering), non-metaheuristic methods, non-hybrid metaheuristic methods and hybrid metaheuristic methods. The advantages, disadvantages, parameter settings, results obtained and listed based on the clustering environmental setting such as mobility, multi-hop data transmission, single-hop data transmission, heterogeneity, and other parameters/environments that are not commonly used. The research gap from the review is outlined to determine the existing problems and limitations in the WSN field.	Web of Science (WoS) indexed journals and articles are used for reviewing the optimizing method of WSN. The expected outcome is to find the research gap in WSN clustering.
RQ: How to achieve exploitation and exploration capabilities in metaheuristic method for global optimum solutions? RO: To develop a hybrid metaheuristic method that balances exploration and exploitation capabilities.	Merge sperm swarm optimization (SSO) and genetic algorithm (GA) in the metaheuristic method, making it a hybrid method (HSSOGA). In HSSOGA, the GA is performed first to ensure that the exploration takes place via crossover and mutation operators followed by the fast nature of SSO to converge into the explored region which allows a balance of exploration and exploitation in search of the global optimum. HSSOGA is evaluated using 11 benchmark test functions based on CEC 2017 test suite consisting of Sphere, Sum Square, Zakharov, Rosenbrock, Step, Griewank, Ackley, Rastrigin, Schwefel 2.26, Michalewicz and EggCrate. The results obtained by the proposed algorithm is compared with existing hybrid algorithms such as HSSOGSA, HFPSO, HPSOGA, SAGA and PSOGWO.	MATLAB R2021a version is used to develop and evaluate the proposed HSSOGA. The expected outcome is to obtain a hybrid algorithm with a balance between exploration and exploitation capability.

Continued on next page

Table 3.1, continued

RQ & RO	**Methodology**	**Technique, Material & Expected outcome**
RQ: How to mitigate the isolated nodes and energy hole problem in clustered WSN? RO: To enhance the cluster head selection and cluster formation by using the adaptive hybrid metaheuristic method.	Since the operators such as mutation, crossover, and velocity ensure an algorithm's exploration and exploitation capability, the proposed method adjusts the operator's probability and speed according to the fitness of the sperm population after the crossover and mutation phase. This is to ensure that exploration and exploitation are well suited to the current state of the network for optimal CH selection and cluster formation. The objective functions for clustering using metaheuristic algorithm are refined to overcome the isolated node and hotspot/energy hole problem where objective such as isolated node probability will reduce the nodes far away to be left out from clusters and objective such as maximum CH's neighbour degree which reduces the selection of CH with many member nodes that may cause the CH to die off quickly that causes network hole in the long term. Re-clustering techniques are enhanced to reduce the re-clustering frequency in the view of reducing the energy consumption overhead caused by the re-clustering process. The proposed modification and algorithm are simulated with a standard environmental setting such as random deployment of 100 nodes on 100m x 100m area with BS located outside of the area.	MATLAB R2021a version is used to simulate the modified proposed method with refined objective functions. The expected outcomes are an improved clustered WSN with reduced energy consumption and efficient data transfer and no nodes die off quickly, and all nodes will belong to a cluster.

Continued on next page

Table 3.1, continued

RQ & RO	Methodology	Technique, Material & Expected outcome
RQ: How to ensure that the network stability and inter-cluster communication are enhanced in clustered WSN? RO: To validate the proposed method used in clustering by evaluating the performance in terms of network lifetime, average residual energy, re-clustering occurrence, total packet delivery, network throughput and end-to-end delay.	The results obtained are based on a few criteria such as average residual, network lifetime in terms of FND, HND and LND and total re-clustering occurrence to analyse the network stability factor. The network total data delivery, network throughput and end-to-end delay results will analyse the inter-cluster communication efficiency factor of the network. The proposed method with modification and refined objectives is compared with several existing hybrid metaheuristic algorithms in the field of WSN, such as HFAPSO, HSAPSO, HGWOSFO and the traditional WSN clustering method LEACH.	Line graphs and bar graphs are used to depict the results and values in a readable format. MATLAB R2021a is used to plot and draw the graphs. The expected outcome from this objective is to ensure the proposed metaheuristic method able to perform well compared to the existing hybrid metaheuristic algorithm in terms of network stability and inter-cluster communication efficiency.

3.4 Chapter Summary

This chapter has discussed the methods used in this work in detail with a clear flow of the research work. Initially, the research gaps are obtained through a literature review from phase 1 of this work, where more than 100 papers and articles are surveyed and reviewed. Upon formulating the problems from the research gaps, objectives are built. The first objective is to develop a hybrid metaheuristic method with a balance of exploration and exploitation. It is done by merging SSO and GA and evaluating it with 11 test functions containing unimodal and multimodal test problems from CEC 2013, CEC 2015, and CEC 2017 test suites. Following the development, the proposed method is enhanced to cater for the real-life optimization problem, which is CH selection and cluster formation in the field of WSN. A new concept of adaptively adjusting the parameters to suit the network's need for exploration and exploitation capability is proposed. Also, a new set of refined selection criteria, such as isolated node probability and maximum CH's neighbour degree, are paid close attention to reduce the isolated node and energy hole problems by selecting the optimal CH and forming optimal clusters. Two enhanced clustering techniques are also enhanced, given reducing energy consumption by reducing the re-clustering frequency. Finally, the proposed enhanced method is evaluated under standard network settings, and the results are compared with some competitively existing metaheuristic methods in the field of WSN to ensure performance superiority. The performance that ensures the stability of the network and inter-cluster communication efficiency in terms of average residual energy, network lifetime, total re-clustering occurrence, total data delivery, network throughput and end-to-end delay of the network are analysed and discussed.

CHAPTER 4: HYBRID METAHEURISTIC METHOD

4.1 Introduction

The growth of technology in the past decade has been tremendous, so these technologies seek to perform optimally for better performance and to be more cost-effective to the world. To address optimization problems, a theory derived from nature or biological systems is translated into mathematical computations called metaheuristic approaches. The term metaheuristic is divided into two parts: meta and heuristic, where meta refers to a high-level methodology and heuristic refers to a technique for solving problems by devising new methods (Gunantara & Nurweda Putra, 2019).

Metaheuristic functions are deemed to obtain good solutions in a reduced amount of time, and they can solve difficult optimization problems (Xu & Zhang, 2014). Metaheuristic methods also have the advantage of exploration and exploitation capability, where exploration is the ability to explore different regions of the global search space that contain optimal solutions, and exploitation is the ability to focus on local regions that are identified by exploration, to obtain current optimal solutions (Cao et al., 2019; Xu & Zhang, 2014; Yang et al., 2013). However, some good metaheuristic methods are found trapped in local optimal solutions rather than global optimal solutions because they do not have balanced exploitation and exploration capabilities (Yang et al., 2013). In the case of producing a balanced exploration and exploitation capability, hybrid metaheuristic methods are introduced.

A hybrid metaheuristic method means combining two distinct algorithms' advantages into forming one new method (Ting et al., 2015). So, it is deemed to have reduced computational cost and implements efficient optimization (Xu & Zhang, 2014). Metaheuristic approaches can be classified into several groups, which are swarm-based metaheuristics, evolutionary-based metaheuristics, physics-based metaheuristics, and human-based metaheuristics (Abdel-Basset et al., 2018; Fausto et al., 2020). As such, several hybrid metaheuristic methods are explained and discussed below.

Firstly, a hybrid method that involves PSO is categorized under swarm-based metaheuristics. In the year 2018, the hybrid firefly and particle swarm optimization (HFPSO) algorithm was introduced by (Aydilek, 2018) and is used to obtain global solutions for computationally expensive numerical problems. This is proposed because of the firefly algorithm (FA) ability to fine-tune the exploitation. However, hybridizing two swarm-based algorithms might not yield the best exploration and exploitation as well as it needs close attention towards the tuning of FA. Besides that, (Şenel et al., 2019) proposes a new hybrid particle swarm optimization and grey wolf optimization (HPSOGWO) algorithm to obtain global solutions by replacing FA with grey wolf optimizer (GWO), which is a swarm-based algorithm as well. GWO is introduced to reduce the solutions from getting trapped into local optima but using GWO yields a higher time complexity which might cost overhead energy consumption in the case of using these algorithms in large-scale networks such as WSN.

PSO is also paired with the well-known GA for its global searching ability, which is known as evolutionary-based metaheuristics. In the year 2016, (Garg, 2016) proposed a hybrid particle swarm optimization and genetic algorithm (HPSOGA). GA's exploration capabilities are convincing because it has crossover and mutation operators that allow the algorithm to explore search regions (global searching) more, eliminating the issue of the solution being trapped in the local optimum by the PSO algorithm. Later, GA's exploration was tried to be merged with a physics-based algorithm called simulated annealing (SA). The hybrid method combining GA and SA is called SAGA, which is proposed to improve network lifetime and energy efficiency in mobile ad-hoc networks (MANETs). However, GA and SA are well known for their exploration capabilities, limiting global and local search ability (Cao et al., 2019).

In the year 2018, a new competitive algorithm called Sperm Swarm Optimization (SSO) was introduced to compete with PSO, and it was deemed to produce better solutions and outperform PSO, which is widely used in literature for its local search capability (exploitation) in several benchmark tests (H. A. Shehadeh et al., 2018, 2019). The first hybrid algorithm created using SSO was the hybrid sperm swarm optimization and gravitational search algorithm (HSSOGSA) to ensure a good balance between exploration and exploitation capabilities for global optimization (H. Shehadeh, 2021). A Hybrid Genetic Algorithm and Sperm Swarm Optimization (HGASSO) was also proposed to optimize multimodal functions (H. A. Shehadeh et al., 2022). Even though the performance seems convincing, the authors did not ensure the performance of the method in unimodal optimizations, as some hybrid algorithms might not perform well in unimodal functions. Moreover, there is no comparison between existing hybrid algorithms that limits the justification of the algorithm's performance.

Selecting appropriate metaheuristics to be hybridized is a step that must be given close attention to, as it contributes to a good balance between exploration and exploitation and also strengthens each other's weaknesses. In this study, we were motivated by the process of the memetic method for clustering to balance the node's load in WSNs, which promotes a better balance between exploration and exploitation, (Chawra & Gupta, 2020). Memetic algorithms can be called an improved GA that is hybridized with local search ability. Since GA has a limitation of slow convergence rate, researchers use a local search such as hill climbing, simulated annealing or tabu search methods to enhance the overall algorithm to reach an optimized solution faster and efficiently (Poonam, 2009; Ryan, 2003).

Moreover, the better performance of SSO compared to PSO and exploration-based operators of GA has motivated us even more to select the Sperm Swarm Optimization (SSO) algorithm and Genetic Algorithm (GA) to be hybridized to achieve a globally optimal solution without drifting away towards local optima in both unimodal and multimodal test functions. The objective of this paper is to develop the Hybrid Sperm Swarm Optimization (SSO) algorithm and Genetic Algorithm (GA) (HSSOGA) and evaluate the developed method with both unimodal and multimodal test functions as well as compare the obtained results with its conventional method and several existing hybrid methods for the best justification upon its performance. The remainder of the chapter is as follows. Section 4.2 will summarize the conventional version of algorithms and the development of the hybrid method. Section 4.3 will discuss the experimental settings and the test function used. The results obtained and brief discussions are depicted in section 4.4 and section 4.5, respectively. Finally, section 4.6 summarizes this chapter.

4.2 Development of Hybrid Metaheuristic Method

This section discusses the conventional algorithms of HSSOGA, which are SSO and GA, in detail with its process flow. Then, a complete process of hybridising the conventional algorithms using the Low-level Teamwork Hybrid (LTH) method is also described in detail.

4.2.1 Conventional Sperm Swarm Optimization (SSO)

Sperm swarm optimization was proposed recently by (H. A. Shehadeh et al., 2018) for wireless sensor network (WSN) challenges. The algorithm was inspired by the natural fertilization process, where a swarm of sperm cells swim towards the ovum to merge with it. During this process, only one out of millions of sperm cells is the winner. In the beginning, the swarm of sperm cells reside in the cervix randomly with two velocities on

X-axis and Y-axis. Figure 4.1 shows an overview of SSO.

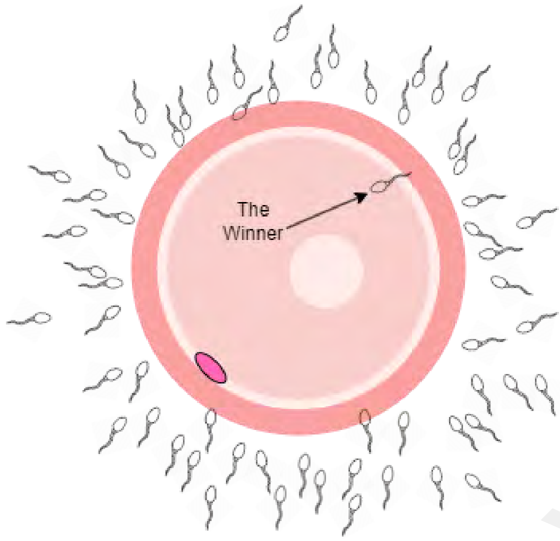

Figure 4.1: Overview of SSO (H. A. Shehadeh et al., 2018)

The behaviour of a swarm of sperm cells swimming towards the ovum exhibits a behaviour similar to "flocking". The movement of sperm is affected by two important parameters, which are pH value and temperature inside the female reproductive system. These two parameters define the sperm's motility and movement direction. According to the findings in (das Neves & Bahia, 2006), the pH value in a female reproductive system is around 4.5 to 5.5, while the temperature inside a female reproductive system can vary between 35.1 °C to 37.4 °C. However, (H. A. Shehadeh et al., 2018) states that the alkaline pH value, which is around 7 to 14, is the most suitable for the sperm's movement, and the temperature in a female reproductive system may go up to 38.5 °C because of the vaginal blood pressure.

To translate this phenomenon in an optimization environment, the sperms act as a candidate solution which moves in the multidimensional search space domain to obtain the global optimal solution. The swarms also record the best solution in their tracks, which means optimal sperm where the globally optimal solution (the sperm that was successful in fertilizing the ovum) and the local optimal solution (sperm optimal solution) are considered.

4.2.2 Conventional Genetic Algorithm (GA)

For the past decade, a plethora of research has used GA as an optimization method for multiple applications such as power electronics, wireless sensor networks, and airline bookings (George et al., 2012; Jun et al., 2006; Norouzi & Zaim, 2014). GA is an algorithm developed by (Holland, 1992) based on Charles Darwin's theory of survival of the fittest, where it is a biological evolution process. GA starts with a population consisting of random chromosomes that are later selected to apply crossover and mutation.

Crossover operators exchange some genes in a specific way from the selected chromosomes that act as the parents to generate new offspring (new solutions) (Katoch et al., 2021). A Uniform crossover operator is adopted in this paper. Uniform crossovers have the advantage of unbiased exploration, and they are applicable to be used on large subsets. However, they produce less diverse solutions.

Mutation operators are used to maintain the diversity of individuals (solutions) from one population to the next population so that the solutions don't get trapped into local optima. The mutation operator works by changing some genes from an individual chromosome, which then results in it carrying different characteristics from their parents (diverse solution) (Katoch et al., 2021).

4.2.3 Proposed Hybrid Sperm Swarm Optimization and Genetic Algorithm (HSSOGA)

Since hybridization consists of two conventional algorithms merging to form a method, this section will briefly describe the inspiration, flow, structure, characteristics, and mathematical modelling of both the conventional SSO and GA algorithms.

Hybrid metaheuristics has become a pivotal approach in solving optimization problems as it promotes a balance between exploration and exploitation. Moreover, a hybrid metaheuristic also reduces the limitation of conventional algorithms, where both algorithms try to cancel out each other's limitations. Hybridization can be done through several cooperative metaheuristic methods, as depicted in Figure 4.2 (Jourdan et al., 2009).

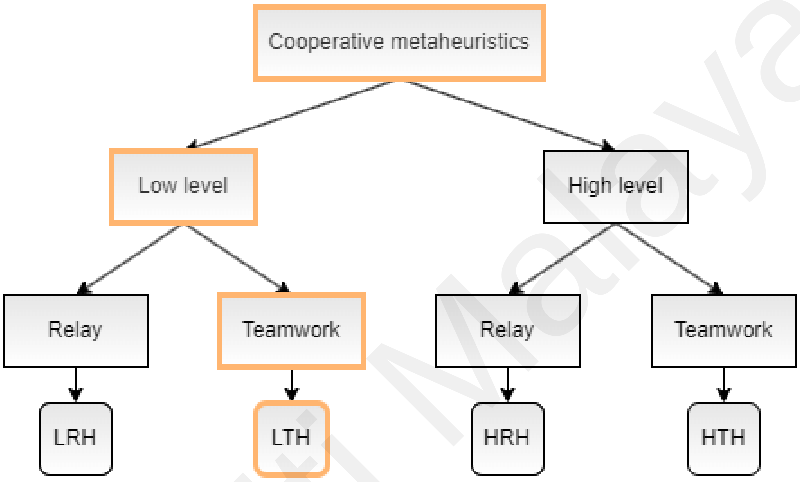

Figure 4.2: The four classes of cooperative metaheuristics: LRH, LTH, HRH, HTH.

A cooperative metaheuristic is designed based on 2 phases which are low-level/high-level and relay/teamwork. The usage of low-level optimization in the first phase is a composite of a single optimization method where another metaheuristic changes a metaheuristic. On the other hand, high-level optimization is a metaheuristic with no direct relationship to its internal processes. In the second phase, using relay hybridization means the metaheuristics are applied one after another creating a sequential process where each uses the previous output as its input. On the other hand, teamwork hybridisation has many parallel cooperating agents where each agent searches in the search domain (Jourdan et al., 2009; Talbi, 2002). So, using low-level optimization in phase 1 and relay hybridization in phase 2 creates Low-level Relay Hybrid (LRH) which is a method that is embedded into another method and executed sequentially. Utilizing low-level optimization with teamwork hybridization creates Low-level Teamwork Hybrid (LTH) where the element of a method is replaced in another method, and it performs parallelly. Moreover, the usage of high-level optimization with relay hybridization yields High-level Relay Hybrid (HRH) where two methods are self-contained and executed sequentially. The last class is called High-level Teamwork Hybrid (HTH) which utilizes the high-level optimization of phase 1 with teamwork hybridization of phase 2. HTH contained methods that are self-contained and works parallelly (Jourdan et al., 2009).

In this research, we hybridize SSO and GA using the Low-level Teamwork Hybrid (LTH) method. LTH allows a method to be embedded into a global method and executed in parallel. Based on (Jourdan et al., 2009), this hybrid method can also be called "Parallel Collaborative Hybrids", where two algorithms are run simultaneously by changing the same population. LTH also allows the two distinct algorithms to work on the initial population and with its operators and bring the fittest population to the next iteration.

Initialization

Initially, all the sperm cells are randomly positioned using a continuous uniform distribution, where each sperm represents a candidate solution. The initial fitness of the population is evaluated and sorted. In this process, the global best, x_{sgBest}, is also updated after the initial evaluation to set as a benchmark for the following iterations.

Selection

In this process, two sperms are selected from the initial population using the "Roulette Wheel" technique, where all the possible chromosomes are attached to the wheel, and the wheel is rotated randomly to select specific chromosomes for the crossover and mutation process (Katoch et al., 2021). The probability, $Prob_i$, of selecting specific individuals using roulette wheel selection is expressed in Eq. (4.1) and Eq. (4.2).

$$Prob_i = \exp\left(\frac{-beta\ .\ Fit_i}{WorstFit_i}\right) \tag{4.1}$$

$$Prob_i = \frac{Prob_i}{\sum_{i=1}^{nPop} Fit_i} \tag{4.2}$$

Where selection pressure, $beta = 8$, Fit_i is the fitness of the chromosome, $WorstFit_i$ is the worst fitness obtained, and $nPop$ is the size of the population.

Crossover and Mutation

Upon selecting the sperm, the crossover process begins, which ends up producing a new population called the crossover population. Following this, the mutation process begins a mutation of the sperm cells from the initial population, producing another new mutated population.

Merge, Sort and Truncate

The populations from crossover and mutation processes are merged and sorted in ascending order of the values. It is then truncated to the number of populations, $nPop$, set at the beginning of the method, to ensure that the best population is obtained.

Velocity and Position Update

The initial sperm velocity, V_0, is calculated using Eq. (4.3).

$$V_0 = Damp\ .\ V_i\ .\ \log_{10}(pH_1) \tag{4.3}$$

Where $Damp$ is the damping factor (0 to 1), V_i is current sperm velocity, and pH_1 is a random pH value between 7 and 14.

The personal best solution is expressed by Eq. (4.4), and the global best solution is expressed by Eq. (4.5).

$$CurrentBestSol(t) = \log_{10}(pH_2) \; . \; \log_{10}(Temp_1) \; . \; (x_{sBest_i} - x_i(t)) \tag{4.4}$$

$$GlobalBestSol(t) = \log_{10}(pH_3) \; . \; \log_{10}(Temp_2) \; . \; (x_{sgBest} - x_i(t)) \tag{4.5}$$

Where pH_2 and pH_3 are random pH values between 7 and 14, $Temp_1$ and $Temp_2$ are random temperature values between 35.1 °C and 38.5 °C, x_{sBest_i} is the personal best location of sperm i at iteration t, x_{sgBest} is the global best location of the sperm (global optimal solution), and x_i is the current location of the sperm at iteration t.

The velocity of the sperm (V_i) is evaluated as per Eq. (4.6).

$$\begin{aligned} V_i = Damp \; . \; V_i \; . \; \log_{10}(pH_1) \\ + \log_{10}(pH_2) \; . \; \log_{10}(Temp_1) \; . \; (x_{sBest_i} - x_i(t)) \\ + \log_{10}(pH_3) \; . \; \log_{10}(Temp_2) \; . \; (x_{sgBest} - x_i(t)) \end{aligned} \tag{4.6}$$

The current position of the sperm (current solution) is calculated as depicted in Eq. (4.7) to ensure that the position updates on each iteration towards achieving the global optimal solution.

$$x_i(t) = x_i(t) + v_i(t) \tag{4.7}$$

To avoid the method from drifting away from the global optima solution, velocity and position limits are applied before evaluating the fitness. The maximum and minimum velocities are calculated in Eq. (4.8) and Eq. (4.9).

$$V_{max} = 0.1 * (Var_{max} - Var_{min}) \tag{4.8}$$

$$V_{min} = -V_{max} \tag{4.9}$$

Where V_{max} is the maximum velocity limit and V_{min} is the minimum velocity limit, and Var_{max} and Var_{min} are the maximum and minimum position limits, respectively. In other words, Var_{max} and Var_{min} are the search domain's maximum and minimum values. The maximum velocity is always kept 10% in between the maximum and minimum velocity limits as smaller random velocities deem to produce better results (Engelbrecht, n.d.)

Upon completing the velocity and position update process, the population is merged, sorted, and truncated again for the next iteration. The population's fitness is then evaluated and updated to see if the values achieved are better than the previous global best solution.

The flow of the overall process of HSSOGA is described in Figure 4.3.

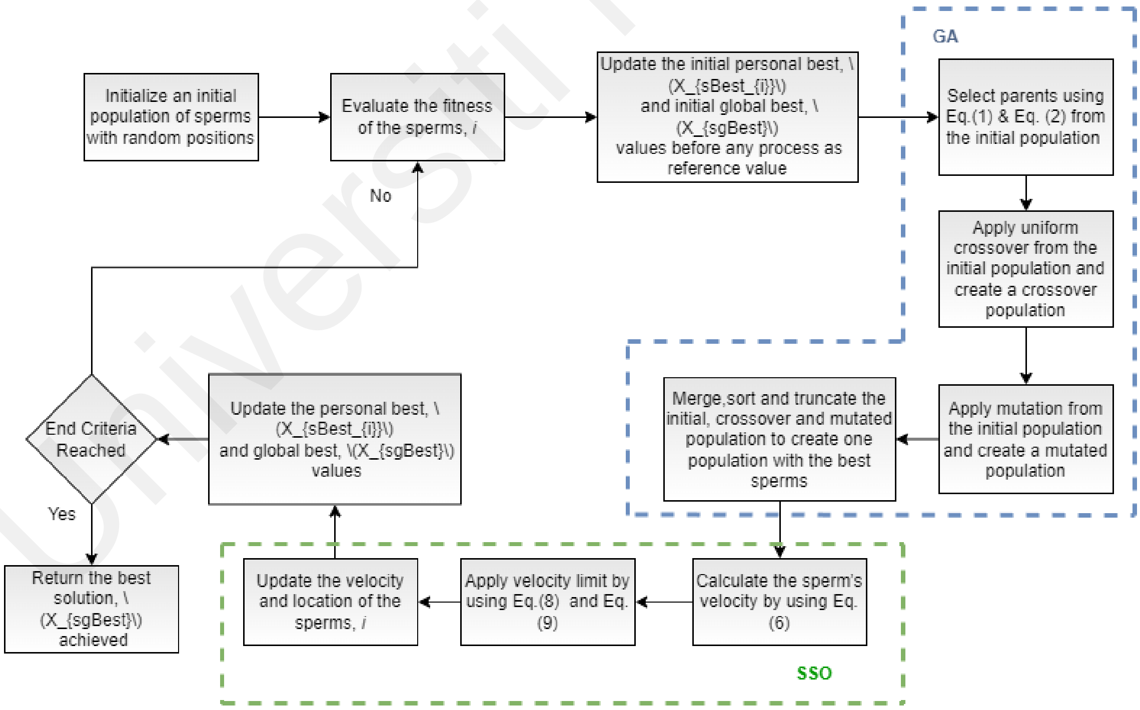

Figure 4.3: The process flow of the proposed HSSOGA.

The overall algorithm of Hybrid Sperm Swarm Optimization and Genetic Algorithm (HSSOGA) is depicted by the pseudocode below:

```
Algorithm 4.1:
Hybrid Sperm Swarm Optimization and Genetic Algorithm (HSSOGA)

Begin
Step 1: Set the number of population (nPop),maximum iteration
   (MaxIter) and iter = 0
Step 2: Initialize the population(sperm,i)and calculate the
   fitness.
Step 3: while (iter < MaxIter)
Step 4: Calculate selection probabilities by using Eq.(4.1) and
   Eq.(4.2)
Step 5: Use Roulette Wheel to SELECT parents.
Step 6: Use Uniform Crossover on the selected parents.
Step 7: Use Mutation.
Step 8: Merge,sort and truncate the population
Step 9: Apply SSO
       for i = 1 : population size do
           Calculate the sperms velocity by using Eq.(4.6)
           Apply velocity limit by using Eq.(4.8) and Eq.(4.9)
           Update the position of the sperm by using Eq.(4.7)
           Apply position limit
       end for
Step 10: Obtain the x_sgBest (Global Optimum Value).
    end while
End.
```

4.3 Experimental Settings

The performance of the proposed HSSOGA is evaluated based on numerical and statistical comparison. To make the comparison fair, HSSOGA is compared with its conventional methods, which are GA and SSO, as well as some existing hybrid methods, such as HPSOGA, PSOGWO, SAGA, HFPSO and HSSOGSA. These comparisons are made from the optimization of some benchmark test functions as described below:

- The benchmark test functions are mathematical numerical functions. The set of numerical functions determines the performance of metaheuristic methods in solving real world problems (Hussain et al., 2017).

- The selected benchmark contains both unimodal and multimodal benchmark functions from CEC' 2013, CEC' 2015 and CEC' 2017 to provide a better performance comparison of the methods (Bala & Yadav, 2020; Cheng et al., 2015; Elsayed et al., 2013; Hashim et al., 2022).
- The selected benchmark functions are also minimization problems where functions 1, 2, 3, 4, 5, 6, 7, 8, 9, and 11 have a minimum optimal value of 0, and function 10 has a minimum optimal value <-9.66015 (Jamil & Yang, 2013; Surjanovic & Bingham, 2013).

To obtain the best fitness, all benchmark test functions are set to standard dimensions and search domain ranges. The dimension for all the functions is set to 30 with a standard population of 100. The search domains are the maximum and minimum positions that the sperms can travel to evaluate performance efficiently without having out-of-bound values (Jamil & Yang, 2013; Surjanovic & Bingham, 2013). The global optimal values are either maximum or minimum optimum values compared to all other possible solution sets (Abdullah & Ahmed, 2020). So, the global optimum values stated in the mathematical test functions are based on the testing by (Surjanovic & Bingham, 2013). The mathematical notion, their range of search space domain, their dimensions and categorization of unimodal and multimodal test functions are described in Appendix A.

The proposed, conventional, and existing methods are programmed in MATLAB R2021a on a computer running Windows 10 Pro with 16GB DDR4 RAM and an AMD Ryzen 5 5600X 6-Core 3.7 GHz processor. All the methods are fed with a standard parameter suggested by the literature. The parameters used by the methods are listed in detail in Table 4.1. The mutation and crossover probabilities are set to 0.3 and 0.7, respectively. On the other hand, the values of c1 and c2 are set to 1.5 based on (Aydilek, 2018; Şenel et al., 2019).

Moreover, the c1, c2 and c3 of the GWO algorithm are set to 0.5 with the inertia weight (w) set at 0.7298 as in (Şenel et al., 2019).

Table 4.1: List of parameters of SSO, GA, HSSOGA, HSSOGSA, HPSOGA, SAGA, HFPSO and PSOGWO

Parameters	Values
HSSOGA	
Velocity damping factor (D)	Rand (0, 1)
Temperature	Rand (35.5, 38.5)
pH	Rand (7, 14)
Crossover Percentage (pc)	0.7
Mutation Percentage (pm)	0.3
Mutation Rate (mu)	0.1
SSO	
Velocity damping factor (D)	Rand (0, 1)
Temperature	Rand (35.5, 38.5)
pH	Rand (7, 14)
GA	
Crossover Percentage (pc)	0.7
Mutation Percentage (pm)	0.3
Mutation Rate (mu)	0.1
HSSOGSA	
Velocity damping factor (D)	Rand (0, 1)
Temperature	Rand (35.5, 38.5)
pH	Rand (7, 14)
α	20
G_0	1
HPSOGA	
Inertia Weight Damping Ratio $wdamp$	0.99
$c1$	1.5
$c2$	1.5
Crossover Percentage (pc)	0.7
Mutation Percentage (pm)	0.3
Mutation Rate (mu)	0.1
SAGA	
Initial temperature ($initTemp$)	1000
Final temperature ($finTemp$)	1
Crossover Percentage (pc)	0.7
Mutation Percentage (pm)	0.3
Mutation Rate (mu)	0.1
HFPSO	
$c1$	1.5

Continued on next page

Table 4.1, continued

Parameters	Values
$c2$	1.5
Inertia weight damping factor (w)	0.9
α	0.2
B_0	2
γ	1
PSOGWO	
$c1$, $c2$, $c3$	0.5
$r1$, $r2$, $r3$	Rand (0,1)
Inertia weight (w)	0.7298

The random values stated in Table 4.1 are controlled random values in the specified ranges, as these values contribute to the significance of the nature-inspired algorithms. Having small random parameter values enables diversity in metaheuristic methods to explore and exploit global solutions.

To validate the performance and efficiency of the methods with accuracy, mean, standard deviation, and best fitness criteria are evaluated. These criteria are described below:

Mean (μ): Mean is used to find the average fitness values after running the method N times to ensure the accuracy of the fitness values obtained, as depicted in Eq. (4.21).

$$\mu = \frac{\sum_{i=1}^{n}(f_i)}{N} \tag{4.10}$$

Where f_i is the fitness of ith sperms, and N is the total number of iterations.

Standard deviation (σ): Standard deviation is used to find the dispersion between the values of the fitness function after running the method for N times, as depicted in Eq. (4.22). This will ensure the convergence rate of the method, where a smaller standard deviation means a better convergence rate as the sperms converge efficiently to their optimal positions.

$$\mu = \sqrt{\frac{\sum_{i=1}^{n}(f_i - \mu)^2}{N - 1}} \tag{4.11}$$

Best fitness (optimal value): Best fitness is obtained by finding the minimum fitness value achieved from running the method N times, as depicted in Eq. (4.23).

$$Best_{fit} = \underset{1 \leqq i \leqq N}{min(f_i)} \tag{4.12}$$

Average best fitness: Average best fitness is calculated by averaging the best fitness values over 30 independent runs, as depicted in Eq. (4.24). This metric is used to determine the resistance of the method from being trapped in local optima.

$$AverageBest_{fit} = \frac{\sum Best_{fit}}{30} \tag{4.13}$$

Where $Best_{fit}$ is the best fitness achieved over N iterations.

4.4 Results

The fitness values over 1000 iterations from the simulations of HSSOGA, GA, SSO, PSOGWO, HFPSO, SAGA, HPSOGA and HSSOGSA are evaluated in terms of mean (μ), standard deviation (σ), best fitness (optimal value), and average best fitness over 30 independent runs are described below:

4.4.1 Comparison with conventional methods

The results are depicted in Tables 4.2 and 4.3, where the best results are shown in bold text. To ensure the convergence of the results, the method is processed 30 independent times on all the benchmark functions.

Table 4.2: The numerical comparison results with conventional methods

Test Function		**SSO**	**GA**	**HSSOGA***
F1	**Best**	**1.74E-251**	1.91E-32	1.71E-160
	Average Best	**2.49E-204**	5.40E-06	1.08E-150

Continued on next page

Table 4.2, continued

Test Function		SSO	GA	HSSOGA*
F2	**Best**	**3.10E-249**	7.90E-32	1.02E-161
	Average Best	**6.21E-193**	7.03E-05	2.41E-146
F3	**Best**	7.25E-80	2.297122519	**4.51E-157**
	Average Best	2.50E-72	25.4494108	**3.34E-147**
F4	**Best**	26.5203676	24.75827686	**22.84251707**
	Average Best	27.46019878	62.23417757	**23.46738764**
F5	**Best**	4.265736337	**0.0000**	**0.0000**
	Average Best	4.706287994	**8.57E-10**	8.28E-09
F6	**Best**	**0.0000**	**0.0000**	**0.0000**
	Average Best	**0.0000**	0.004446813	**0.0000**
F7	**Best**	**8.88E-16**	7.99E-15	**8.88E-16**
	Average Best	1.01E-15	4.40E-05	**8.88E-16**
F8	**Best**	**0.0000**	9.07E-06	**0.0000**
	Average Best	**0.0000**	0.003673853	**0.0000**
F9	**Best**	8642.733457	947.5072532	**947.5070587**
	Average Best	9569.462714	1654.189346	**1575.230715**
F10	**Best**	-6.297533967	**-29.3050437**	-28.27425892
	Average Best	-4.197229975	**-26.00042022**	-25.7070616
F11	**Best**	-45.29747145	**-45.29761135**	**-45.29761135**
	Average Best	-45.13970782	**-45.29761135**	**-45.29761135**

* = Proposed Method

Table 4.3: The statistical comparison results with conventional methods

Test Function	SSO		GA		HSSOGA*	
	μ	σ	μ	σ	μ	σ
F1	135.429	2319.162	330.3047	2829.527	**72.48017**	**1195.676**
F2	2141.296	34324.59	4460.717	38324.1	**1197.833**	**20002.23**
F3	3073.699	97098.5	10134.05	315380.8	**4.749502**	**34.06526**
F4	290755	6615326	618321.2	8309928	**107015.4**	**2621449**
F5	114.5638	2011.76	330.0602	2859.767	**70.72267**	**1171.976**
F6	1.245399	21.82383	2.910744	23.14966	**0.733629**	**11.44752**
F7	0.245736	1.707526	0.609113	2.48301	**0.167571**	**1.341744**
F8	**2.867999**	**23.85509**	18.01666	45.59172	5.663088	29.45629
F9	8642.733	**1.46E-10**	1524.119	1552.319	**1474.353**	1439.745
F10	-6.29753	**4.53E-14**	**-26.353**	4.222277	-25.2374	4.416332
F11	-45.2934	0.057219	-45.2964	0.033638	**-45.2967**	**0.017091**

* = Proposed Method

The explanation of obtained results from numerical comparison with conventional methods are explained as follows:

- In optimizing functions 1 and 2, SSO outperformed GA and HSSOGA. This is because both functions are unimodal function, which has one local/global optimal point. This kind of optimization needs more exploitation capabilities to converge into optimal results. Since HSSOGA and GA have mutation and crossover operators, this makes the sperms and chromosomes not converge to obtain the best fitness values, as it creates a diverse population.
- However, the proposed HSSOGA outperformed GA in optimizing functions 3, 4, 7, and 9 while it outperformed SSO in optimizing functions 3, 4, 5, and 9. This is because the mutation and crossover operator that is embedded in HSSOGA helps the method to solve complex mathematical formulas of these functions efficiently with optimized fitness values. The exploitation capability of SSO and the exploration capability of GA create a balanced environment in HSSOGA, allowing it to perform well in both unimodal and multimodal functions.
- Moreover, GA outperformed SSO and HSSOGA in function 10 because it's a scalable function that needs more exploration and diversity of mutation and crossover operations. The fast nature of SSO does not optimize function 10 efficiently.

As an overall summary, we can see that HSSOGA has the best optimal value for 8 out of 11 test function problems, SSO has the best fitness on 5 out of 11 test function problems, and GA has the best optimal value for 4 out of 11 test function problems. On the other hand, the average best fitness value of 30 independent runs shows that HSSOGA is the best in 7 out of 11 test function problems, SSO is the best in 4 out of 11 test function problems, and GA is the best in 3 out of 11 test function problems. From the results, we can conclude that HSSOGA outperformed GA and SSO in 2 unimodal and six multimodal functions (3, 4, 6, 7, 8, 9, and 11) to obtain the best fitness.

The explanation of obtained results from statistical comparison with conventional methods are explained as follows:

- The proposed HSSOGA outperformed both its conventional GA and SSO in functions 1, 2, 3, 4, 5, 6, 7, 9, and 11 in terms of convergence rate. This is because the combination of the fast-paced sperms and the inclusion of mutation and crossover of the chromosomes produces a balanced method that converges faster in most of the functions.
- HSSOGA can also be seen as stable in functions 1, 2, 3, 4, 5, 6, 7, and 11, as they have a smaller dispersion between the values.
- However, SSO shows a smaller dispersion of fitness values in optimizing functions 8, 9 and 10. This is because SSO faces smaller dispersion because it falls into local optimum in functions 9 and 10, as depicted in Table 4.2, which are deemed to be multimodal functions.

As an overall summary, we can conclude that HSSOGA has a smaller dispersion and faster convergence rate in 8 out of 11 test function problems, SSO has a faster convergence rate in 1 out of 11 test function problems, and GA has a faster convergence rate in 1 out of 11 test function problems, as depicted in Figure 4.4 (a-k), with mean values in Table 4.3. So, it can be said that HSSOGA outperformed SSO and GA in all five unimodal and three multimodal functions in terms of stability of achieving the best fitness and faster convergence rate.

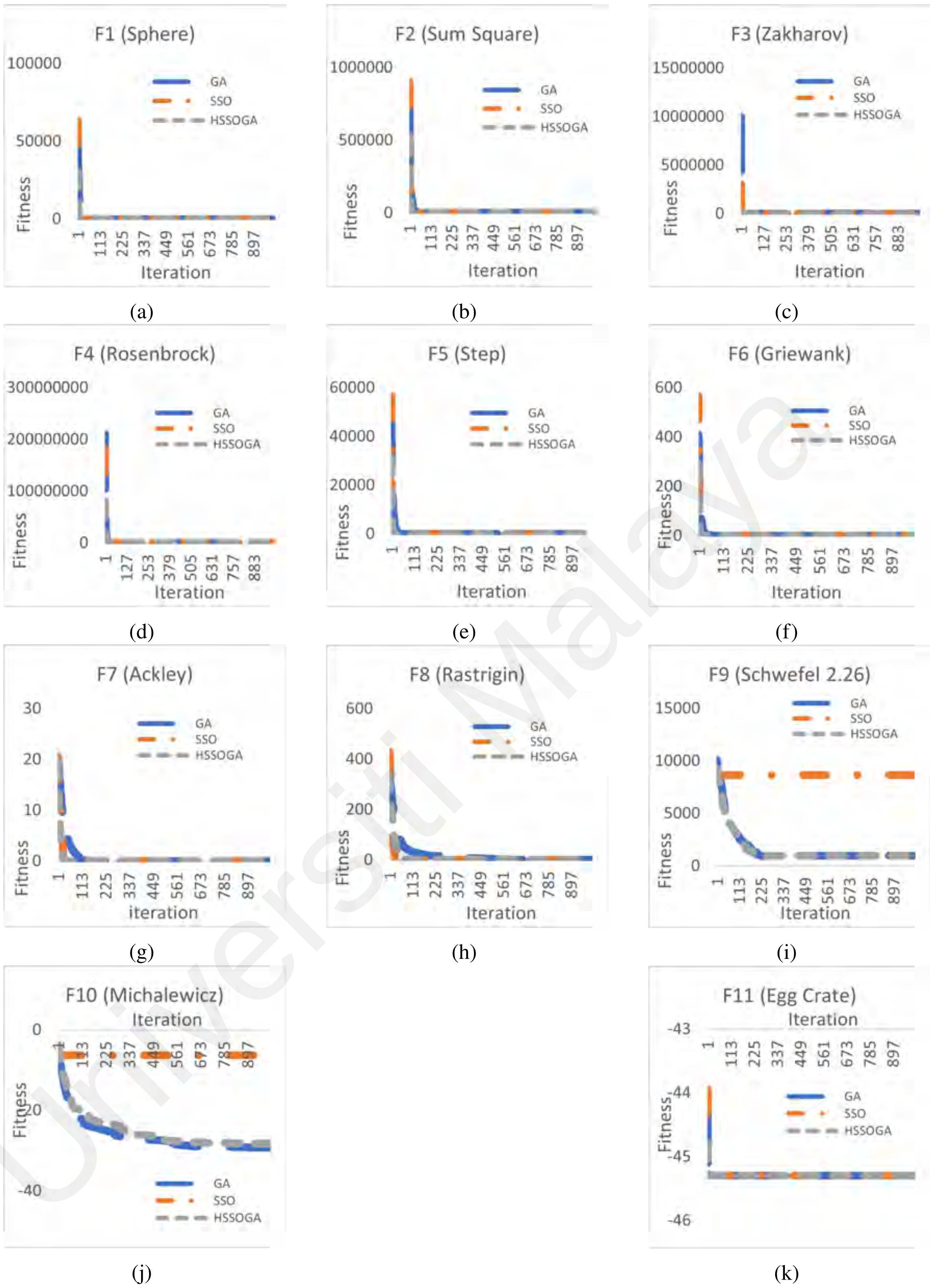

Figure 4.4: (a-k) Comparison of the convergence rate with conventional methods

To ensure the significance of results from the conventional methods comparison, a statistical analysis called One-way ANOVA with Post Hoc Tukey's test was carried out as depicted in Table 4.4.

Table 4.4: Statistical analysis of results using "One-way ANOVA (Tukey's test)" between HSSOGA and the conventional methods

Test Function	Algorithm (I)	Algorithm (J)	Mean Difference (I-J)	p-Value (Sig.)
F1	HSSOGA	GA	**-257.82457***	**0.026***
		SSO	-62.94885	0.802
F2	HSSOGA	GA	-3262.88436	0.057
		SSO	-943.4629	0.786
F3	HSSOGA	GA	-10129.2968	0.46
		SSO	-3068.9494	0.931
F4	HSSOGA	GA	-511305.798	0.166
		SSO	-183739.662	0.792
F5	HSSOGA	GA	**-259.33753***	**0.018***
		SSO	-43.8411	0.89
F6	HSSOGA	GA	**-2.17711***	**0.034***
		SSO	-0.51177	0.828
F7	HSSOGA	GA	**-0.44154***	**< 0.001***
		SSO	-0.07816	0.629
F8	HSSOGA	GA	**-12.35357***	**< 0.001***
		SSO	2.79509	0.161
F9	HSSOGA	GA	-49.76584	0.634
		SSO	**-7168.3801***	**< 0.001***
F10	HSSOGA	GA	**1.11559***	**< 0.001***
		SSO	**-18.93990***	**< 0.001***
F11	HSSOGA	GA	-0.00038	0.975
		SSO	-0.00333	0.145
*. The mean difference is significant at the 0.05 level.				

The proposed HSSOGA has outperformed the compared GA in test functions 1, 5, 6, 7, 8, and 10. This is because the optimal value achieved by HSSOGA from simulations proves that it is better than GA in most of the benchmark test functions. Besides, HSSOGA has a significant performance improvement towards GA in high ranges multimodal search space such as functions 6 and 9 as the p-Value and mean differences of HSSOGA and the conventional methods are significant at the 0.05 level. HSSOGA has also outperformed the compared SSO in test functions 9 and 10, yielding significant optimal values in these multimodal test function problems.

4.4.2 Comparison with existing methods

The results are depicted in Tables 4.5 and 4.6, where the best results are shown in bold text. To ensure the convergence of the results, the method is processed 30 independent times on all the benchmark functions.

Table 4.5: The numerical comparison results with existing hybrid methods

Test Function		HFPSO	HPSOGA	SAGA
F1	**Best**	2.56E-16	7.93E-61	9.88E-34
	Average Best	2.57E-15	2.53E-55	1.55E-06
F2	**Best**	3.80E-15	8.91E-60	8.06E-31
	Average Best	5.03E-14	3.70E-54	2.61E-06
F3	**Best**	5.02E-06	1.25E-08	10.47547543
	Average Best	0.000118845	1.01E-06	40.54598855
F4	**Best**	**9.748974018**	13.27780311	24.6857928
	Average Best	34.22436546	31.24158055	102.7739149
F5	**Best**	6.48E-17	**0.0000**	1.45E-31
	Average Best	2.07E-15	**2.05E-33**	1.22E-05
F6	**Best**	5.55E-16	**0.0000**	**0.0000**
	Average Best	0.008611388	0.001395855	0.002547124
F7	**Best**	7.87E-09	7.99E-15	7.99E-15
	Average Best	2.79E-08	1.90E-14	9.19E-06
F8	**Best**	22.88401797	**0.0000**	5.85E-06
	Average Best	44.40827769	9.56E-06	0.00232185
F9	**Best**	3770.361081	1065.945393	1065.945393
	Average Best	5000.556758	**1547.594621**	1575.230519
F10	**Best**	-20.9167687	**-29.11364757**	-28.47474317
	Average Best	-17.09591952	**-27.10084291**	-26.46601774
F11	**Best**	**-45.29761135**	**-45.29761135**	**-45.29761135**
	Average Best	**-45.29761135**	**-45.29761135**	-45.29760766
Extension of this table is as below				
Test Function		**PSOGWO**	**HSSOGSA**	**HSSOGA***
F1	**Best**	1.80E-56	7.83E-19	**1.71E-160**
	Average Best	467.7724477	1.26E-18	**1.08E-150**
F2	**Best**	1.67E-50	1.35E-17	**1.02E-161**
	Average Best	13430.95666	2.33E-17	**2.41E-146**
F3	**Best**	1.40E-33	4.33E-18	**4.51E-157**
	Average Best	31.44696487	7.22E-18	**3.34E-147**
F4	**Best**	24.74482611	19.89568571	22.84251707
	Average Best	3978382.442	53.25170091	**23.46738764**
F5	**Best**	1.67E-06	7.15E-19	**0.0000**
	Average Best	1658.638777	1.27E-18	8.28E-09
F6	**Best**	**0.0000**	**0.0000**	**0.0000**
	Average Best	22.63170768	0.018247602	**0.0000**

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Table 4.5, continued

Test Function		PSOGWO	HSSOGSA	HSSOGA*
F7	**Best**	2.58E-14	5.87E-10	**8.88E-16**
	Average Best	3.139933571	0.075724197	**8.88E-16**
F8	**Best**	5.304967577	53.7276325	**0.0000**
	Average Best	106.0308325	94.88555354	**0.0000**
F9	**Best**	2920.004998	2689.178397	**947.5070587**
	Average Best	5076.574427	3913.916748	1575.230715
F10	**Best**	-19.50307577	-17.48954989	-28.27425892
	Average Best	-13.25439421	-13.96881241	-25.7070616
F11	**Best**	**-45.29761135**	**-45.29761135**	**-45.29761135**
	Average Best	-45.29714592	**-45.29761135**	**-45.29761135**

* = Proposed Method

Table 4.6: The statistical comparison results with existing hybrid methods

Test Function	HFPSO		HPSOGA		SAGA	
	μ	σ	μ	σ	μ	σ
F1	316.8884	2118.202	82.39804	**961.6036**	280.9659	2555.935
F2	3787.125	27152.86	1204.006	**14691.19**	4237.507	38202.84
F3	20849.44	392909.9	6.718748	**26.1917**	187.3455	4528.75
F4	209665.8	3462915	114522.8	2751861	555880.4	6719246
F5	309.3069	1978.174	97.06827	**1114.291**	280.9695	2526.345
F6	2.820574	16.23711	0.977843	**10.95433**	3.530839	27.2045
F7	1.782764	2.910557	0.404207	1.75225	0.645342	2.644395
F8	45.74981	44.22613	11.74978	34.23369	18.1789	45.06898
F9	4206.01	932.7171	**1395.08**	1077.531	1661.989	1559.321
F10	-16.1301	5.230045	**-25.7479**	4.235901	-25.2285	4.229054
F11	-45.2964	0.021993	**-45.2967**	0.031072	**-45.2967**	**0.014717**
Extension of this table is as below						
Test Function	**PSOGWO**		**HSSOGSA**		**HSSOGA***	
	μ	σ	μ	σ	μ	σ
F1	309.3164	2724.529	496.3401	3843.228	**72.48017**	1195.676
F2	3091.436	34630.06	5993.163	50129.45	**1197.833**	20002.23
F3	104616.5	3302224	4516.313	142115.6	**4.749502**	34.06526
F4	298773.4	4466997	1103406	11063074	**107015.4**	**2621449**
F5	169.2135	2041.5	333.0854	3102.99	**70.72267**	1171.976
F6	4.775141	28.01791	3.906253	31.02391	**0.733629**	11.44752
F7	0.688493	2.729284	0.713476	2.468824	**0.167571**	**1.341744**
F8	55.54386	85.72036	77.20287	54.18906	**5.663088**	**29.45629**
F9	6609.242	1826.896	2923.363	**758.1194**	1474.353	1439.745
F10	-15.8209	**2.548888**	-14.7504	3.436212	-25.2374	4.416332
F11	-45.2768	0.248754	-45.2915	0.090301	**-45.2967**	0.017091

* = Proposed Method

The explanation of obtained results from numerical comparison with existing hybrid methods are explained as follows:

- HFPSO outperformed HPSOGA, SAGA, PSOGWO, HSSOGSA and proposed HSSOGA in optimizing function 4, which is a unimodal valley-shaped function. The exploitation capability of the firefly algorithm and PSO algorithms yields good optimization. However, this does not apply to other test functions.
- In optimizing a few multimodal test functions, the HPSOGA method shows good competition to the proposed HSSOGA as the structure of the methods are similar, but HPSOGA uses particles compared to HSSOGA's sperms. It shows great performance in achieving the best fitness in function 10 with the best average fitness score in function 9. It also shows equal performance to HSSOGA in functions 5, 6, 8 and 11.
- The proposed HSSOFA has outperformed most of the existing hybrid methods in test functions 1, 2, 3, 7 and 9 while equal best in optimizing function 6 with HPSOGA, SAGA, PSOGWO and HSSOGSA. However, HSSOGA showed the best average of 0.0000, which means the method is stable and did not fall into local optima over 30 independent runs. On the same note, HSSOGA has the best average in function eight compared to HPSOGA, even though both methods show the same best results, which justifies the stability of HSSOGA.

As an overall summary of the obtained results, HSSOGA has the best fitness for 9 out of 11 test function problems and has the optimal fitness value in 5 out of 11 test function problems. HFPSO, SAGA, PSOGWO, and HSSOGSA have the best fitness for 2 out of 11 test function problems. By looking at the average best values after 30 independent runs, it can be concluded that HSSOGA is the best in 8 test functions, HPSOGA is the best in 4 test functions, and HFPSO and HSSOGA are the best in 1 of the 11 test functions. On the other hand, SAGA and PSOGWO did not have a good average best value in all the test function problems. So, the proposed HSSOGA can be highlighted as the best-performing method out of the 11 benchmark test functions.

The explanation of obtained results for statistical comparison with existing hybrid methods are explained as follows:

- From the mean results, it can be said that HSSOGA outperformed HFPSO, HPSOGA, SAGA, PSOGWO, and HSSOGSA by obtaining the best average fitness values over 1000 iterations for the test functions 1, 2, 3, 4, 5, 6, 7, and 8 showing a good central tendency of the fitness value.
- HPSOGA has achieved a smaller dispersion in values (standard deviation) in test functions 1, 2, 3, 5 and 6 because the method's PSO of HPSOGA might control the movement of the particles as there are no affecting parameters such as pH value and temperature of SSO in HSSOGA. However, the standard deviation values of HSSOGA are not a huge amount of difference as well compared to HPSOGA.
- HPSOGA outperformed all the compared hybrid methods in test functions 9 and 10. HPSOGA, SAGA, and HSSOGA had the same average fitness value for function 11 in achieving the best mean fitness values.
- So, HSSOGA has a smaller value dispersion on functions 4, 7, and 8, while HPSOGA has a smaller value dispersion on functions 1, 2, 3, 5, and 6. These dispersion values show the stability of the method on the functions stated above.

As an overall summary, we can say that the proposed HSSOGA has a smaller dispersion in relation to the mean in 3 out of 11 test functions compared to other methods, while HPSOGA has smaller dispersion in values in 5 out of 11 test functions. HSSOGSA, PSOGWO and SAGA methods have smaller dispersion values in 1 out of 11 test functions each. Besides, HSSOGA has the best central tendency in 9 out of 11 test functions, while the top competitor has the best central tendency in 3 out of 11 test functions. The convergence rate of these methods is depicted in Figure 4.5(a-k). As such, it can be concluded that HSSOGA performs better than all the existing methods in 5 unimodal and four multimodal functions by achieving good central tendency and not huge dispersion of values over 1000 iterations.

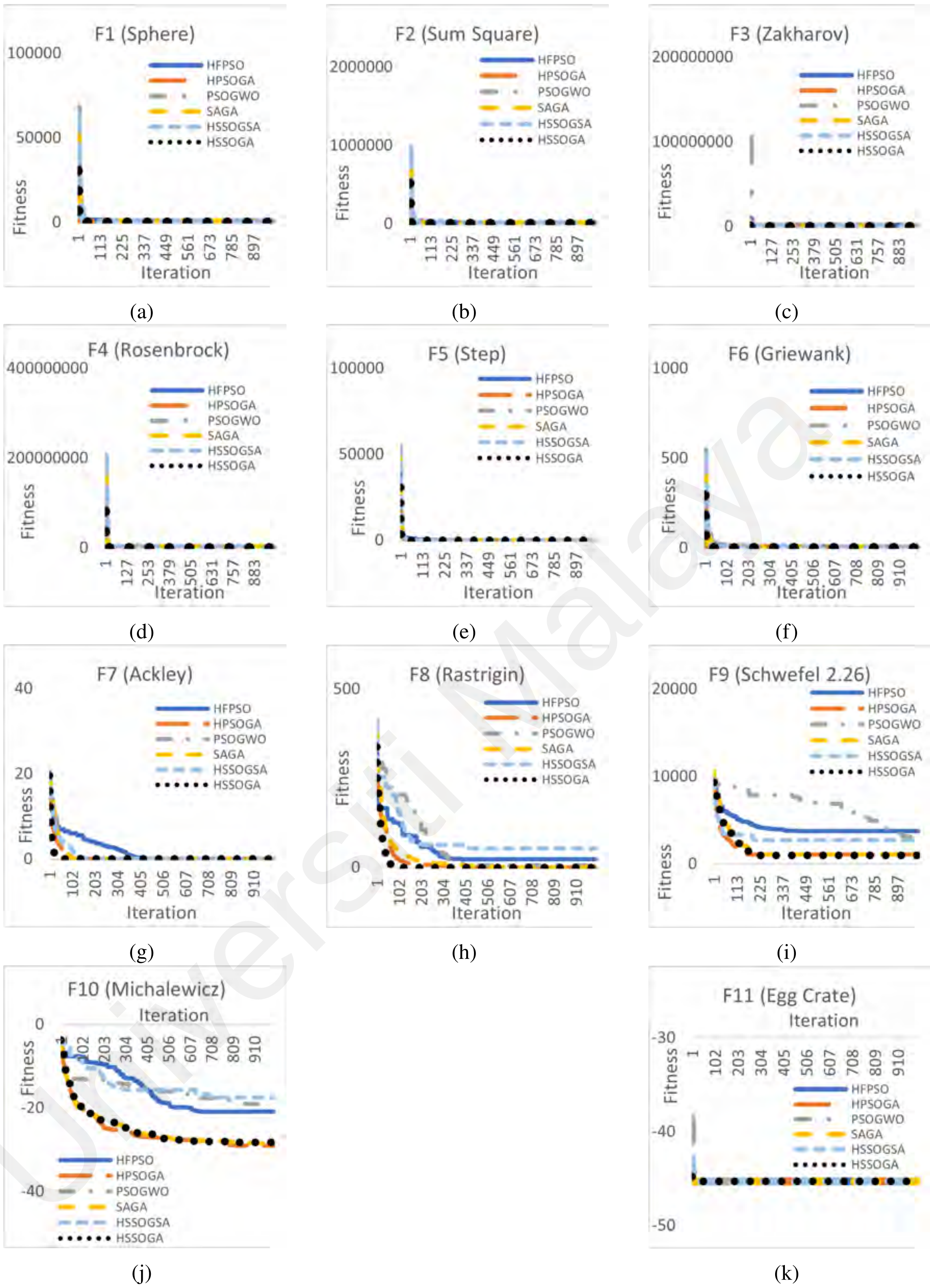

Figure 4.5: (a-k) Comparison of the convergence rate with existing hybrid methods

To ensure the significance of results from the comparison of the existing methods, a statistical analysis called One-way ANOVA with Post Hoc Tukey's test was carried out as depicted in Table 4.7.

Table 4.7: Statistical analysis of results using "One-way ANOVA (Tukey's test)" between HSSOGA and the existing methods

Test Function	Algorithm (I)	Algorithm (J)	Mean Difference (I-J)	p-Value (Sig.)
F1	HSSOGA	HFPSO	-244.40819	0.218
		HPSOGA	-9.91786	1.000
		PSOGWO	-236.83622	0.250
		SAGA	-208.48569	0.393
		HSSOGSA	**-423.85994***	**0.001***
F2	HSSOGA	HFPSO	-2589.29187	0.495
		HPSOGA	-6.17303	1.000
		PSOGWO	-1893.60315	0.794
		SAGA	-3039.67396	0.308
		HSSOGSA	**-4795.3297***	**0.015***
F3	HSSOGA	HFPSO	-20844.69	0.999
		HPSOGA	-1.97	1.000
		PSOGWO	-104611.78	0.518
		SAGA	-182.60	1.000
		HSSOGSA	-4511.56	1.000
F4	HSSOGA	HFPSO	-102650.39	0.999
		HPSOGA	-7507.39	1.000
		PSOGWO	-191758.02	0.980
		SAGA	-448864.98	0.545
		HSSOGSA	**-9223.37***	**0.003***
F5	HSSOGA	HFPSO	-238.58424	0.116
		HPSOGA	-26.34559	1.000
		PSOGWO	-98.49086	0.903
		SAGA	-210.24683	0.225
		HSSOGSA	-262.36277	0.061
F6	HSSOGA	HFPSO	-2.08694	0.295
		HPSOGA	-0.24421	1.000
		PSOGWO	**-4.04151***	**0.001***
		SAGA	-2.79721	0.058
		HSSOGSA	**-3.17262***	**0.019***
F7	HSSOGA	HFPSO	**-1.61519***	**< 0.001***
		HPSOGA	-0.23664	0.225
		PSOGWO	**-0.52092***	**< 0.001***
		SAGA	**-0.47777***	**< 0.001***
		HSSOGSA	**-0.54590***	**< 0.001***
F8	HSSOGA	HFPSO	**-40.08672***	**< 0.001***
		HPSOGA	-6.08669	0.095
		PSOGWO	**-49.88077***	**< 0.001***
		SAGA	**-12.51581***	**< 0.001***
		HSSOGSA	**-71.53978***	**< 0.001***
F9	HSSOGA	HFPSO	**-2731.6565***	**< 0.001***

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Table 4.7, continued

Test Function	Algorithm (I)	Algorithm (J)	Mean Difference (I-J)	p-Value (Sig.)
		HPSOGA	79.27356	0.761
		PSOGWO	**-5134.8882***	**< 0.001***
		SAGA	**-187.63607***	**0.019***
		HSSOGSA	**-1449.0094***	**< 0.001***
F10	HSSOGA	HFPSO	**-9.10732***	**< 0.001***
		HPSOGA	0.51047	0.060
		PSOGWO	**-9.41652***	**< 0.001***
		SAGA	-0.00891	1.000
		HSSOGSA	**-10.48700***	**< 0.001***
F11	HSSOGA	HFPSO	-0.00027	1.000
		HPSOGA	-0.00074	1.000
		PSOGWO	**-0.01992***	**0.001***
		SAGA	-0.00005	1.000
		HSSOGSA	-0.00528	0.891
***. The mean difference is significant at the 0.05 level.**				

The proposed HSSOGA only outperformed and obtained significance values compared to HSSOGSA in unimodal test functions 1, 2, and 4. However, the significance of multimodal test functions is an important analysis as most of the real-world situations are deemed to be solving complex multimodal problems. So, HSSOGA outperforms most of the existing hybrid methods in multimodal test functions 6, 7, 8, 9, and 10, which proves that it has a good capability of avoiding local optima compared to other existing hybrid methods. Since HPSOGA is a close competitor, HSSOGA does not yield any significance value from the One-way ANOVA (Tukey's test), but it still yields better fitness, and the balanced exploration and exploitation capability shows that the method does not fall into local optima easily from its numerical average best fitness results which credit as an outperformer of HPSOGA.

4.4.3 Comparison of execution runtimes

Runtimes of a method show the ability of the method to compute the best fitness in a duration of time (Weise et al., 2014). Shorter runtime means the method is less complex, while longer runtime shows that the method is more complex. The average execution runtimes of the methods in eleven test functions are compared in Table 4.8. The average execution runtimes, R_{ave}, are calculated using the equation Eq. (4.25).

$$R_{ave} = \frac{\sum(R/30)}{11} \tag{4.14}$$

The average execution runtimes, R_{ave}, are evaluated based on 30 independent runs of each metaheuristic method over 1000 iterations each on eleven test functions are calculated to ensure its performance.

Table 4.8: The average execution runtimes of the proposed, conventional, and exiting methods

Algorithms	Average execution runtimes over 11 test functions (seconds)
GA	1.870322
SSO	1.546674
HFPSO	0.706595
HPSOGA	3.738738
PSOGWO	0.486333
SAGA	2.193528
HSSOGSA	8.465875
HSSOGA*	3.698654

* = Proposed Method

The table shows that the proposed HSSOGA takes a slightly longer average execution runtime compared to its conventional methods. However, compared to the existing memetic method (HPSOGA), the proposed method has a shorter execution runtime. This shows that selecting SSO for the local search enables faster runtimes compared to the well-known PSO. The longer execution over 1000 iterations is caused by the crossover and mutation operators of GA to find the local optimum efficiently. HSSOGA is still considered efficient because it converges towards the local optimum faster based on Figures 4.4 and 4.5, which directly reduces the average execution runtime to achieve the global optimum in most test functions.

4.4.4 Boundary Performances

The average best results shown in Tables 4.2 and 4.5 depicts the average results over 30 independent runs. Boundary performance shows the closeness of the values obtained over 30 independent runs to justify the evaluated results depicted above. Table 4.9 shows the boundary performances of all the compared algorithms.

Table 4.9: Boundary performances of all the compared algorithms

Test Function	Algorithm	Max	Min	Diff (Max - Min)
F1	GA	1.05E-04	1.91E-32	1.05E-04
	SSO	5.58E-203	1.74E-251	5.58E-203
	HFPSO	8.22E-15	2.56E-16	7.97E-15
	HPSOGA	5.32E-54	7.93E-61	5.32E-54
	SAGA	3.98E-05	9.88E-34	3.98E-05
	PSOGWO	6.10E+03	1.80E-56	6.10E+03
	HSSOGSA	1.78E-18	7.83E-19	9.97E-19
	HSSOGA	1.89E-149	1.71E-160	1.89E-149
F2	GA	2.09E-03	7.90E-32	2.09E-03
	SSO	1.86E-191	3.10E-249	1.86E-191
	HFPSO	3.40E-13	3.80E-15	3.36E-13
	HPSOGA	5.09E-53	8.91E-60	5.09E-53
	SAGA	2.84E-05	8.06E-31	2.84E-05
	PSOGWO	3.31E+05	1.67E-50	3.31E+05
	HSSOGSA	3.34E-17	1.35E-17	1.99E-17
	HSSOGA	7.23E-145	1.02E-161	7.23E-145
F3	GA	5.71E+01	2.30E+00	5.48E+01
	SSO	5.02E-71	7.25E-80	5.02E-71
	HFPSO	1.02E-03	5.02E-06	1.01E-03
	HPSOGA	6.36E-06	1.25E-08	6.35E-06
	SAGA	1.04E+02	1.05E+01	9.36E+01
	PSOGWO	3.10E+02	1.40E-33	3.10E+02
	HSSOGSA	1.07E-17	4.33E-18	6.39E-18
	HSSOGA	5.43E-146	4.51E-157	5.43E-146
F4	GA	1.43E+02	2.48E+01	1.18E+02
	SSO	2.89E+01	2.65E+01	2.37E+00
	HFPSO	8.24E+01	9.75E+00	7.27E+01
	HPSOGA	7.73E+01	1.33E+01	6.40E+01
	SAGA	1.13E+03	2.47E+01	1.11E+03
	PSOGWO	5.39E+07	2.47E+01	5.39E+07
	HSSOGSA	2.87E+02	1.99E+01	2.67E+02

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Table 4.9, continued

Test Function	Algorithm	Max	Min	Diff (Max - Min)
	HSSOGA	2.39E+01	2.28E+01	1.07E+00
F5	GA	2.21E-08	0.00E+00	2.21E-08
	SSO	4.99E+00	4.27E+00	7.24E-01
	HFPSO	1.12E-14	6.48E-17	1.11E-14
	HPSOGA	9.24E-33	0.00E+00	9.24E-33
	SAGA	3.61E-04	1.45E-31	3.61E-04
	PSOGWO	2.63E+04	1.67E-06	2.63E+04
	HSSOGSA	1.61E-18	7.15E-19	8.94E-19
	HSSOGA	2.35E-07	0.00E+00	2.35E-07
F6	GA	3.69E-02	0.00E+00	3.69E-02
	SSO	0.00E+00	0.00E+00	0.00E+00
	HFPSO	5.15E-02	5.55E-16	5.15E-02
	HPSOGA	1.72E-02	0.00E+00	1.72E-02
	SAGA	1.48E-02	0.00E+00	1.48E-02
	PSOGWO	2.82E+02	0.00E+00	2.82E+02
	HSSOGSA	8.03E-02	0.00E+00	8.03E-02
	HSSOGA	0.00E+00	0.00E+00	0.00E+00
F7	GA	7.40E-04	7.99E-15	7.40E-04
	SSO	4.44E-15	8.88E-16	3.55E-15
	HFPSO	9.28E-08	7.87E-09	8.49E-08
	HPSOGA	1.57E-13	7.99E-15	1.49E-13
	SAGA	2.67E-04	7.99E-15	2.67E-04
	PSOGWO	1.92E+01	2.58E-14	1.92E+01
	HSSOGSA	1.34E+00	5.87E-10	1.34E+00
	HSSOGA	8.88E-16	8.88E-16	0.00E+00
F8	GA	1.74E-02	9.07E-06	1.74E-02
	SSO	0.00E+00	0.00E+00	0.00E+00
	HFPSO	9.55E+01	2.29E+01	7.26E+01
	HPSOGA	2.62E-04	0.00E+00	2.62E-04
	SAGA	9.67E-03	5.85E-06	9.67E-03
	PSOGWO	3.16E+02	5.30E+00	3.11E+02
	HSSOGSA	1.51E+02	5.37E+01	9.75E+01
	HSSOGA	0.00E+00	0.00E+00	0.00E+00
F9	GA	2.72E+03	9.48E+02	1.78E+03
	SSO	1.01E+04	8.64E+03	1.48E+03
	HFPSO	6.46E+03	3.77E+03	2.68E+03
	HPSOGA	2.01E+03	1.07E+03	9.48E+02
	SAGA	2.13E+03	1.07E+03	1.07E+03
	PSOGWO	9.76E+03	2.92E+03	6.84E+03
	HSSOGSA	5.36E+03	2.69E+03	2.67E+03
	HSSOGA	2.49E+03	9.48E+02	1.54E+03
F10	GA	-2.25E+01	-2.93E+01	6.84E+00
	SSO	-3.33E+00	-6.30E+00	2.96E+00
	HFPSO	-1.39E+01	-2.09E+01	7.05E+00
	HPSOGA	-2.42E+01	-2.91E+01	4.87E+00

Continued on next page

Table 4.9, continued

Test Function	Algorithm	Max	Min	Diff (Max - Min)
	SAGA	-2.35E+01	-2.91E+01	5.54E+00
	PSOGWO	-6.12E+00	-1.95E+01	1.34E+01
	HSSOGSA	-1.02E+01	-1.75E+01	7.24E+00
	HSSOGA	-2.07E+01	-2.83E+01	7.58E+00
F11	GA	-4.53E+01	-4.53E+01	0.00E+00
	SSO	-4.41E+01	-4.53E+01	1.16E+00
	HFPSO	-4.53E+01	-4.53E+01	0.00E+00
	HPSOGA	-4.53E+01	-4.53E+01	0.00E+00
	SAGA	-4.53E+01	-4.53E+01	1.11E-04
	PSOGWO	-4.53E+01	-4.53E+01	1.12E-02
	HSSOGSA	-4.53E+01	-4.53E+01	0.00E+00
	HSSOGA	-4.53E+01	-4.53E+01	0.00E+00

The above table summarizes the boundary performance of each metaheuristic method in each test function. The PSOGWO have performed poorly in all the test function which shows the instability of the algorithm which means it did not achieve global optimum values efficiently. However, the proposed method managed to score very consistent best values over 30 independent runs as it has an approximation of 0.00E+00 in test functions 6, 7, 8, and 11 where it shows that HSSOGA is performing stable in multimodal test functions. It also recorded approximation below the value of 1 and close to 0 in test functions 1, 2, 3, and 5 which concludes that the proposed method is stable in unimodal test functions as well.

4.4.5 Overall Results Summary

The overall results are summarized by ranking all the methods in terms of the mean fitness value obtained. The ranking summary is presented in Table 4.9. From Table 4.9, we can conclude that HSSOGA outperformed all the other compared methods in 8 out of 11 test function problems, where it shows a good quality of balance between exploration and exploitation in a method. However, in functions 7 and 8, where these functions are highly multimodal, HSSOGA is ranked second. This is because the method possesses a high velocity of the SSO, which makes the method miss the global optimum in earlier stages. For function 9, the test function has valleys that make it difficult to search. As such, GA, which has a good exploration characteristic, manages to find the best fitness efficiently, whereases HSSOGA is ranked third, as merging fast SSO compromises the exploration of GA slightly.

Table 4.10: Methods ranking based on the statistical results

Test Function	SSO	GA	HFPSO	HPSOGA	SAGA	PSOGWO	HSSOGSA	HSSOGA*
F1	3	7	6	2	4	5	8	**1**
F2	3	7	5	2	6	4	8	**1**
F3	4	6	8	2	3	7	5	**1**
F4	5	8	4	3	7	6	2	**1**
F5	3	7	6	2	5	4	8	**1**
F6	3	5	4	2	6	8	7	**1**
F7	2	4	8	3	5	6	7	**1**
F8	**1**	4	6	3	5	7	8	2
F9	8	3	6	**1**	4	7	5	2
F10	8	**1**	5	2	4	6	7	3
F11	6	4	4	**1**	**1**	8	7	**1**

* = Proposed Method

4.5 Chapter Discussion

In this chapter, a hybrid metaheuristic method is proposed called the Hybrid Sperm Swarm Optimization and Genetic Algorithm (HSSOGA) to solve optimization problems and to solve real-world problems in future of this research. This method is proposed to have a balanced exploration and exploitation based on two distinct algorithms, which are SSO and GA. Based on the results in Table 4.2 to Table 4.7, it can be said that the proposed HSSOGA has a good performance and convergence rate compared to other compared algorithms. Besides, HSSOGA can also jump out of local optima to reach the global optima efficiently with the characteristic of good exploration from mutation and crossover operators as well as good exploitation from the fast-paced sperm motility in search of the ovum. Furthermore, HSSOGA yields better fitness and average fitness in many multimodal test functions such as Griewank, Ackley, Rastrigin, Schwefel and Michalewicz functions in achieving the near-to-global optimum fitness values. So, achieving a constant best average value shows that the method is more stable upon deployment in solving problems by avoiding the local minima because of its good exploration and exploitation capabilities. However, this phenomenon might change in the real world, constantly changing environments where the adaptive capability of tuning the mutation and crossover probability would help in better use of the method in future.

The compared hybrid methods taken from the literature, which are HFPSO, HSSOGSA, SAGA, PSOGWO and HPSOGA, are utilized for results comparison to ensure the performance validity of the proposed HSSOGA in solving both unimodal and multimodal tests functions. Methods such as HFPSO, PSOGWO and HPSOGA use a similar exploitation-based algorithm called PSO to exploit the searched regions and use different algorithms to cater for the exploration part. On the other hand, HSSOGSA uses SSO for exploitation but uses GSA as an exploration factor but from the results, we can see that HSSOGA has been performing significantly better compared to it. This observation shows the importance of selecting the appropriate algorithm to hybrid to ensure that the algorithms' advantages would yield better performance.

The novelty of this study is to develop a hybrid metaheuristic method with balanced exploration and exploitation where two distinct algorithms work in parallel to obtain the fittest population for each round. It allows the merging, sorting and trunking of the population produced by both SSO and GA so that the fittest are evaluated for the next round. Besides, the analysis of the method also contributes to the novelty of this method as many proposed hybrid methods only consider multimodal optimization, but to justify the performance of our proposed hybrid method, both unimodal and multimodal optimization is used to determine the efficiency of the method to deduce the conclusion on achieving the balanced exploration and exploitation.

Since the results and quality of results favour the proposed HSSOGA, it can be used in many real-world scenarios for optimization such as healthcare systems, Wireless Sensor Networks (WSNs), and engineering fields, as it has a good capability to handle high search ranges and complex problems as it optimizes Griewank and Schwefel functions with high search domains.

4.6 Chapter Summary

This chapter has discussed the importance of building a hybrid metaheuristic method in solving optimization functions. Initially, some non-hybrid metaheuristic methods are analysed from the literature review on selecting two distinct algorithms with good exploration and exploitation capabilities. Genetic Algorithm (GA) and Sperm Swarm optimization (SSO) algorithm is selected for their exploration and exploitation capability to merge their ability to form a hybrid metaheuristic method. The process flow and steps of the method are also discussed in detail, which tells the importance and advantages of the proposed HSSOGA method. A set of 11 optimization benchmark test functions are selected based on CEC 2013, CEC 2015, and CEC 2017 test suite which are Sphere (F1), SumSquare(F2), Zakahrov (F3), Rosenbrock (F4), Step (F5), Griewank (F6), Ackley (F7), Rastrigin (F8), Schwefel (F9), Michalewicz (F10), EggCrate (F11). Out of the 11 test benchmark functions, five is deemed to be unimodal test function which has one local optima and six multimodal functions, that has multiple local minima. This is to test the tendency of the proposed hybrid metaheuristic (HSSOGA) in solving real-world problems later on. To ensure the fairness of results, there were two categories of comparing where in one category, HSSOGA is compared with the conventional SSO and GA algorithms where the results are depicted in Tables 4.2 and 4.3. In contrast, in the other category, HSSOGA is compared with several existing hybrid methods such as HFPSO, HPSOGA, SAGA, PSOGWO and HSSOGSA, which the results are depicted in Tables 4.5 and 4.6. The result analysis is also categorized into two analysis styles, which are numerical comparisons and statistical comparisons. To ensure the significance of the results obtained, a One-way ANOVA (Tukey's test) is also performed, and the results are depicted in Tables 10 and 13. From the results, we learn that HSSOGA outperformed many algorithms in terms of jumping the local optima and achieving the global solution with a good convergence rate. HPSOGA is also deemed to be a close competitor of HSSOGA. Even though HSSOGA does not show a significant difference in statistical analysis, the numerical analysis shows that HSSOGA is stable and continuously produces the best fitness values, as seen in Table 4.5. To conclude the experiment, an overall results summary shows that HSSOGA achieved rank 1 in optimizing most of the test functions.

CHAPTER 5: ADAPTIVE HYBRID METAHEURISTIC METHOD IN WSN

5.1 Introduction

Wireless sensor nodes are unique creations by humans because of their nature of being small and able to carry out tasks that ease the analysis in many fields. For example, these sensor nodes are deployed on a large scale for environmental monitoring to avoid soil erosion and landslides, military applications on communications and threat detections, and medical applications for monitoring for better diagnostics and information tracking (Kingsley Eghonghon et al., 2020). These nodes also utilize a shared spectrum of Industrial, Scientific and Medical (ISM) bands where communication devices such as ZigBee and Wi-Fi are fitted for short communication ranges and LoRa for long communication ranges (A. I. Ali & Zorlu Partal, 2022; Hisham Ahmad, 2018; H. Luo et al., 2015).

Furthermore, sensor nodes are capable of being implemented in the applications mentioned above because they perform certain processes by gathering sensory information and transferring the gathered data with other connected sensor nodes in a network field efficiently. This is possible because sensor nodes are also called a type of transducer that uses a specific amount of energy and signals and transforms data to a readable format to be analysed by the end user (Shakshuki et al., 2009). An internal structure of a sensor node is depicted in Figure 5.1 below, where four components named sensing unit, processing unit, transceiver unit and power unit are the foundation of a sensor node (Matin & Islam, 2012).

Amidst the popular use of sensor nodes in many applications, it has a few concerning limitations that need attention. Due to the sensor node's small architecture, the power unit's energy is limited as some applications are deployed for long-term uses (O. Ali et al., 2022). Changing batteries (power unit) is not a viable option, as well as these WSNs, are deployed on large scales and in places that are difficult for human intervention. Besides, memory

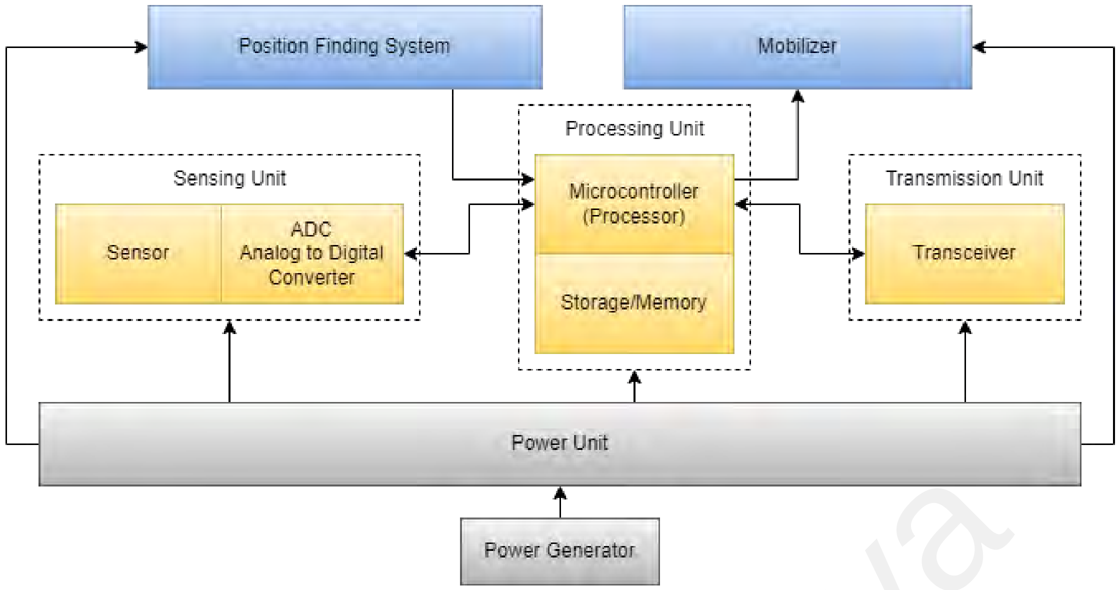

Figure 5.1: The internal structure/component of a sensor node (Matin & Islam, 2012; Negi, 2015)

storage is also limited because of its small form factor where nodes tend to use memory to store the data collected and its routing to the base station to deliver the information (Mekki et al., 2019).

To overcome these limitations of the nodes, many methods of clustering are introduced, as in the literature discussed in Chapter 2 of the thesis. Among the methods, LEACH is the most popular method for clustering. However, it has a few limitations, such as random CH selection may reduce the network lifetime of WSNs, as such many modified and extended versions were also introduced, as discussed in section 2.2.2. of chapter 2. The latest research on clustering also shows the positive effect of using metaheuristic and hybrid metaheuristic methods where a better CH selection and cluster formation technique have lesser energy consumption and preserve the network lifetime, as discussed in sections 2.4 to 2.6 of Chapter 2. These methods focus on maximizing the energy efficiency of the network by using metaheuristics to reduce overhead computational cost and to obtain an optimized solution (selecting the appropriate CH) (Xu & Zhang, 2014).

Even though a lot of improvement has been made to the clustering of WSN, there are still some existing issues that must be given attention which is the hotspot problem and isolated node problem. Hotspot problems are mainly caused by the method of selecting CH that is close to BS, where the nodes closer to BS die quickly, creating a network hole near BS. This affects the network transmission as the nodes' energy drains out much quicker compared to other nodes due to the excessive transmission from other nodes (Khalaf et al., 2022). Prior studies also show that many studies focus on applying unequal clustering to ensure that the hotspot problem can be mitigated by allowing the CH near BS to have lesser member nodes associated with it, but a survey done by (Khalaf et al., 2022) concludes that unequal clustering is not as efficient as static and equal clustering as it causes different issues that are related to overhead and connectivity. On the other hand, isolated nodes are sensor nodes that are not clustered into any clusters and transmit the data directly to BS, where it becomes an obvious issue when the distance between the isolated node and BS is fairly far. This problem is caused by the improper selection of CH and cluster formations (Kalaivani & Indhumathi, 2016).

To mitigate the aforementioned problem, this chapter focuses on enhancing better clustering through adaptive exploration and exploitation of the proposed metaheuristic in Chapter 4 and refining the objective functions for appropriate CH selection and cluster formation. An adaptive exploration and exploitation of a method is vital when it comes to real-time applications. This is because, in WSN, the number of nodes and the energy values keep changing adaptively over time which needs better adjustment of the parameters to yield an optimized solution without being trapped into local optima values. As per the literature discussed in section 2.7 of chapter 2, tuning the parameters of a method would unlock a better solution depending on the application.

In this chapter, six methods in clustering of WSN, namely, Low-Energy Adaptive

Clustering Hierarchy (LEACH), Hybrid Harmony Search Algorithm with Particle Swarm Optimization (HSAPSO), Hybrid Firefly Algorithm with Particle Swarm Optimization (HFAPSO), Hybrid Grey Wolf Optimizer and Sunflower Optimization (HGWOSFO) and newly proposed Hybrid Sperm Swarm Optimization and Genetic Algorithm (HSSOGA) as well as Adaptive Hybrid Sperm Swarm Optimization and Genetic Algorithm (aHSSOGA) are applied. This chapter focuses on the adaptiveness of the proposed HSSOGA with a set of refined objective functions to achieve optimal solutions (optimal CHs). The new set of objective functions consists of the average distance between candidate CHs and other candidate CHs average distance between the candidate CHs and member nodes in a cluster, the average residual energy of the candidate CHs, candidate CH's maximum neighbour node degree and average isolated node probability. The inclusion of these new enhancements is believed to reduce the hotspot problem and isolated node problem occurrence in a WSN system. The remainder of this chapter is as follows: Section 5.2 discusses the WSN model and the assumptions considered. Section 5.3 describes the enhancement of the mechanism of adaptive parameter tuning for adaptive exploration and exploitation of proposed HSSOGA. In section 5.4 discusses new sets of objective function and fitness calculations to select appropriate CH. The cluster head selection, cluster formation and multi-hop routing phases of the proposed WSN system are discussed in section 5.5. The implementation of the proposed method, experimental setup and the simulation steps are described in section 5.6. Finally, in section 5.7, a brief chapter summary is described.

5.2 WSN Model and Application

This thesis adopts the decentralisation method to ensure the entire clustered network is energy efficient. Decentralization is also known to be scalable and efficient compared to the centralized method, as many applications on WSN consider scalability and large-scale networks (Al-Hattab et al., n.d.).

Agriculture contributes significantly to the world by producing food essentials. The ever-growing technology ensures that this agriculture can be more efficient with the use of technology in the form of WSN. Traditional agriculture consists of processes such as planting, fertilisation, and harvesting, which are determined by using a schedule. The active intervention of technology allows smart decisions on these processes by collecting data to monitor weather, air and soil quality which is now known as precision agriculture (Le & Tan, n.d.). The application was adopted by (Qureshi et al., 2020) and implemented optimised clustering called Gateway Clustering Energy-Efficient Centroid (GCEEC). The sensor node deployment for precision agriculture is depicted in the figure below:

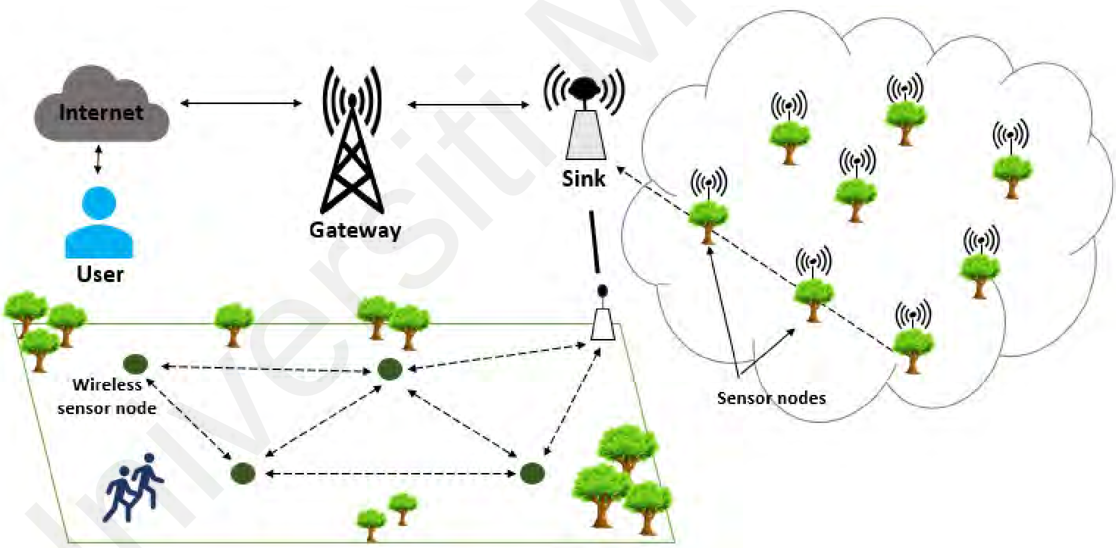

Figure 5.2: The WSN precision agriculture architecture (Qureshi et al., 2020)

The cluster's energy level and centroid position is used to select CH in this clustering. From the results, it is concluded that the proposed method was able to improve the network lifetime, throughput and energy consumption. However, clustering using metaheuristics will give an upper hand in selecting more appropriate CHs and extend the network lifetime. So this thesis adopts precision agriculture application in simulating the WSN networks.

5.2.1 Assumptions of WSN model

WSN comprises many sensor nodes that are usually scattered and difficult to be accessed. So, it can be said that the number of nodes, n, are randomly deployed in $M * N$ in a meters field that can be either square or rectangular field. Each node is deployed statically, and all the nodes are homogenous, with an equal number of energies initially. These nodes are deployed to monitor a particular environment and transfer their data to nodes or sink routed by the multi-hop routing technique. Every data transfer done by a sensor node will exhaust certain energy from the node based on the distance of data transfer, d. All nodes are also uniquely identified with an id. Some other assumptions of the proposed WSN model are listed below:

- The field of deployed WSN has no interferences or objects in the sensing field.
- All nodes can become a CH.
- The base station (sink) is located outside of the sensing field.
- The death of a node is caused by energy depletion only.

The main objective of this model is to ensure that the nodes exhaust the least energy routing the sensed data to sink through the appropriate CH selected across the n number of nodes deployed.

5.2.2 Energy model

In this research, we adopted the first order radio energy consumption model as used in LEACH (W. R. Heinzelman et al., 2000). Every transmission and receiving of data from a node over a distance d will exhaust the energy of a node. Initially, the crossover distance (threshold distance), $d0$, is calculated as follows (Kajal & Goyal, 2016; Yousif et al., 2018).

$$d0 = \sqrt{\frac{E_{fs}}{E_{amp}}} \tag{5.1}$$

Where $d0$ is the crossover distance, E_{fs} is the transmitter amplifier energy for free space and E_{amp} is the transmitter amplifier energy for multi-path.

The nodes that transmit data for a distance more than $d0$ exhaust more energy than the transmission distance lower than d0. The energy dissipation during the transmission of data for both normal nodes and cluster heads is depicted in the equation below (Kajal & Goyal, 2016; Yousif et al., 2018):

$$E_{TX}(k,d) = \begin{cases} k * E_{elec} + k * E_{fs} * d^2, & d < d0 \\ k * E_{elec} + k * E_{amp} * d^4, & d \geq d0 \end{cases} \tag{5.2}$$

Where E_{TX} is the transmission energy for a node, E_{elec} is the energy consumed to transmit or receive a single bit of data, and k is the number of bits in a packet of data.

The dissipation of energy by cluster nodes during reception is calculated as follows:

$$E_{RX} = (E_{elec} + E_{DA}) * k \tag{5.3}$$

Where E_{RX} is the consumed reception energy and E_{DA} is the data aggregation energy for the cluster heads.

The energy parameters values that are used in the First Order Radio model are depicted in Table 5.1.

Table 5.1: First Order Radio model energy parameters values

Parameters	Value
E_{elec}	$50nJ/bit$
E_{amp}	$100pJ/bit/m^2$
E_{fs}	$0.013pJ/bit/m^4$
E_{DA}	$5nJ/bit$
k	$4000bits$

5.3 Proposed Adaptive HSSOGA

According to the literature review in section 2.7 of chapter 2, it can be said that parameter tuning has a great impact on the performance of a metaheuristic method. A WSN is a large-scale optimization problem involving many criteria, which motivates implementing an adaptive parameter tuning to provide a better exploration and exploitation of HSSOGA through the ever-changing energy values and several nodes throughout the sensing period.

The Crossover operator in GA can adjust the exploitation capability of the method while the mutation operator of GA adjusts the exploration of the method (Y. Y. Wong et al., 2003). On the other hand, SSO's velocity speed also contributes to changes in exploration and exploitation values. Faster-paced sperms tend to explore new regions because it randomly moves at high speed, which skips the local optima solutions, while slower-paced sperms exploit towards the global solution in an explored region (Chen et al., 2011; Mathi & Chinthamalla, 2019).

So, in contrast to the ability to control exploration and exploitation of a metaheuristic method to obtain a good global solution, the proposed HSSOGA in Chapter 4 is enhanced with the adaptive ability to select optimal CH in WSN systems.

The crossover and mutation must ensure their probability keeps adaptively changing based on the operator's performance on the initial population. In this way, the probabilities can be adjusted to ensure the best global optimum is reached. The adaptive crossover and mutation probability calculation is depicted below:

$$pc = \begin{cases} pc + 0.001, & \text{if } fitCrossInit_{ave} < fitCross_{ave} \\ pc + 0.001, & \text{if } fitCrossInit_{ave} < fitCross_{ave} \\ pc, & \text{if } fitCrossInit_{ave} = fitCross_{ave} \end{cases} \tag{5.4}$$

$$pm = \begin{cases} pm + 0.001, & \text{if } fitMutInit_{ave} < fitMut_{ave} \\ pm + 0.001, & \text{if } fitMutInit_{ave} < fitMut_{ave} \\ pm, & \text{if } fitMutInit_{ave} = fitMut_{ave} \end{cases} \tag{5.5}$$

Where pc is the crossover probability, pm is the mutation probability, $fitCrossInit_{ave}$ is the average initial population fitness of parents before crossover process, $fitCross_{ave}$ is the average population fitness after crossover process, $fitMutInit_{ave}$ is the average initial population fitness of parents before mutation process and $fitMut_{ave}$ is the average population fitness after mutation.

For better exploitation, the velocity of the sperm should be lower compared to the exploration phase. It is important for a method to explore the search region first before exploiting into a global optimal solution. As such, the velocity dampening factor is gradually reduced over the maximum iteration to ensure the method finds the true global optimum and skips the local optimum. Dampening factors are values in the range of (0,1). The linear decrement of velocity dampening calculation is as follows:

$$Decrement = \frac{1}{MaxIt} \tag{5.6}$$

$$Damp = Damp - Decrement \tag{5.7}$$

Where $MaxIt$ is the maximum iteration of the proposed metaheuristic method and $Damp$ is the dampening factor which starts from the value 1, which means no dampening effect in the beginning as it forces to have exploration and the reduction in dampening factor makes the entire velocity of the sperm slower as shown in the velocity calculation of SSO below:

$$
\begin{aligned}
V_i &= Damp \ . \ V_i \ . \ \log_{10}(pH_1) \\
&+ \log_{10}(pH_2) \ . \ \log_{10}(Temp_1) \ . \ (x_{sBest_i} - x_i(t)) \\
&+ \log_{10}(pH_3) \ . \ \log_{10}(Temp_2) \ . \ (x_{sgBest} - x_i(t))
\end{aligned} \tag{5.8}
$$

Where V_i is the velocity of ith sperm, pH_1, pH_2 and pH_3 are random pH values between 7 to 14, $Temp_1$ and $Temp_2$ are the random temperature values ranging between 35.1 °C and 38.5 °C, x_{sBest_i} is the personal best location of ith sperm, x_{sgBest} is the best global position of the sperm and x_i is the current location of the ith sperm at iteration t.

The overall pseudocode of adaptive Hybrid Sperm Swarm Optimization and Genetic Algorithm is depicted below:

Algorithm 5.1:
Adaptive Hybrid Sperm Swarm Optimization & Genetic Algorithm (aHSSOGA)

Begin
Step 1: Set the number of population ($nPop$),maximum iteration ($MaxIter$) and $iter$=0
Step 2: Set the probability of Mutation, pm=0.3,probability of Crossover, pc=0.7 and $Damp$=1.
Step 3: Initialize the population($sperm, i$)and calculate the fitness.
Step 4: **while**($iter < MaxIter$)
Step 5: Calculate selection probabilities by using **Eq.(4.1)** and **Eq.(4.2)** in Chapter 4.
Step 6: Use Roulette Wheel to **SELECT** parents.
Step 7: Calculate the average fitness of selected parents before crossover, $fitCrossInit_{ave}$.
Step 8: Use **Uniform Crossover** on the selected parents.
Step 9: Calculate the average fitness of selected parents after crossover, $fitCross_{ave}$.
Step 10: Calculate the average fitness of selected parent before mutation, $fitMutInit_{ave}$.
Step 11: Use **Mutation**.
Step 12: Calculate the average fitness of selected parents after mutation, $fitMut_{ave}$.
Step 13: Merge,sort and truncate the population

Step 14: Calculate the velocity dampening factor, $Damp$ using **Eq.(5.6)** and **Eq.(5.7)**.
Step 15: Apply SSO
    for $i = 1 : population\ size$ **do**
        Calculate the sperms velocity by using **Eq.(5.7)**
        Apply velocity limit by using **Eq.(4.8)** and **Eq.(4.9)** as in chapter 4
        Update the position of the sperm by using **Eq.(4.7)** as in chapter 4
        Apply position limit
    end for
Step 16: Obtain the x_{sgBest} value.
Step 17: Update pc and pm according to **Eq.(5.4)** and **Eq.(5.5)**
  end while
End.

The overall process flow of adaptive HSSOGA is described in Figure 5.3 below:

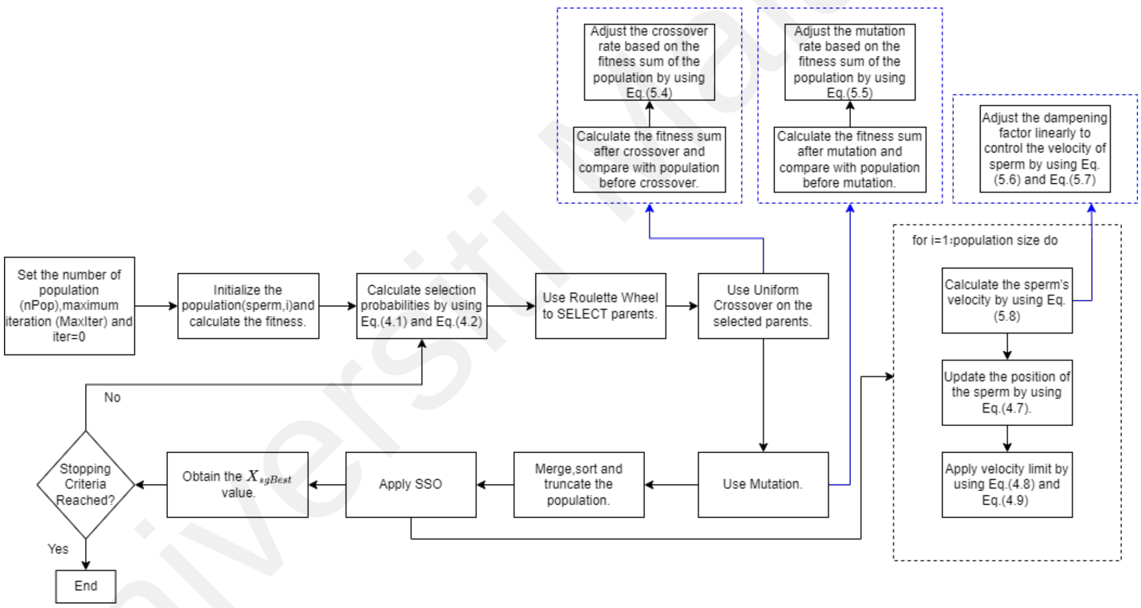

Figure 5.3: The process flow of the proposed adaptive HSSOGA

5.4 Proposed Objective function

To ensure the fitness of each deployed particle, this study proposes a set of refined objective functions/criteria that are needed for the proposed adaptive HSSOGA to optimize. The objective function of this work is more focused on solving the hotspot and isolated node problem that causes deterioration of the quality of WSN in terms of network stability and communication. The population of HSSOGA are deployed randomly in a 2D vector with x and y coordinates ranging between 0 to the WSN area are defined. The optimal positions for CH are selected based on the mapping of the 2D population towards the randomly deployed nodes in the 2D area of sensing. An example of the mapping is depicted in Figure 5.4.

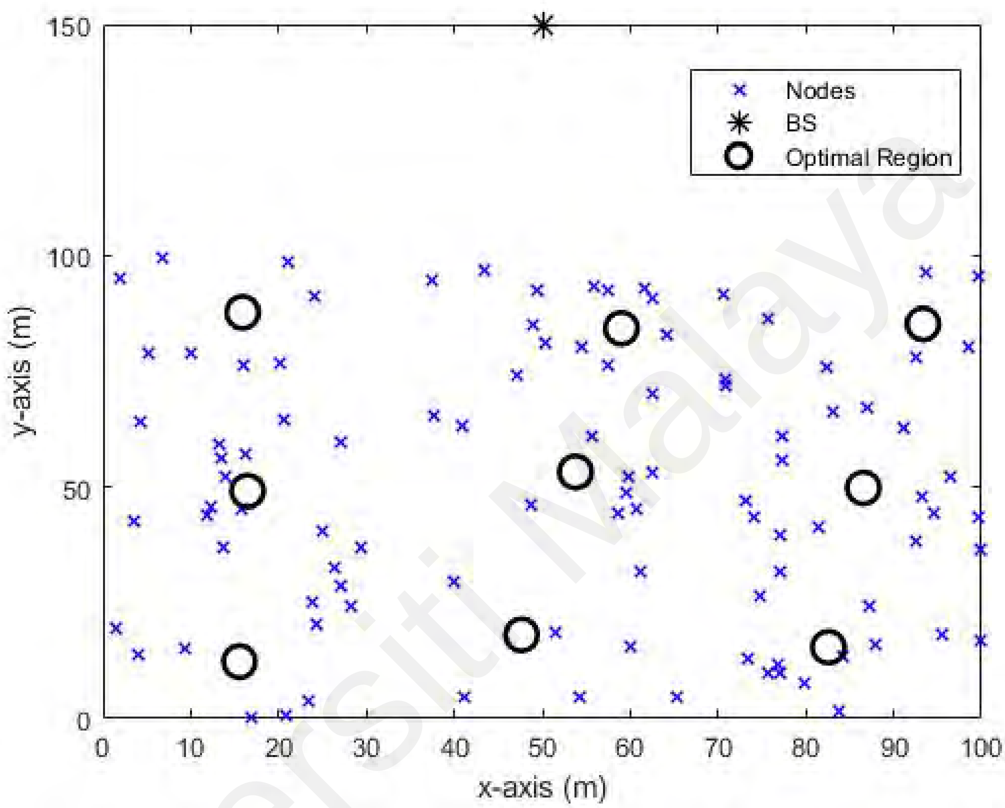

Figure 5.4: Mapping of optimal points of adaptive HSSOGA on WSN nodes

Detailed explanations of the objective function used are given below:

Objective 1: The average distance between candidate CHs and another candidate CHs, $dist(CH_i, CH_j)_{ave}$. This is an important objective as it ensures that the CH selected is not too close to the other CH to ensure that the clusters are not formed too close to each other and reduce the possibility of forming isolated nodes. Besides, it also eliminates the early node death near BS, which causes an energy hole. The objective is calculated as in

Eq.(5.9) and Eq.(5.10).

$$dist(CH_i, CH_j)_{min} = min(\sqrt{(CH_i - CH_j)^2}) \tag{5.9}$$

$$dist(CH_i, CH_j)_{ave} = \frac{\sum_{i=1}^{n_{ch}}(dist(CH_i, CH_j)_{min})}{n_{ch}} \tag{5.10}$$

Where CH is the potential cluster heads at ith and jth position in the sensing field and n_{ch} is the number of potential cluster head nodes.

Objective 2: The average distance between the candidate CHs and member nodes in a cluster, $dist(CH_i, MN_j)_{ave}$. This objective ensures that the CHs selected cover the entire field of nodes deployed to avoid possible isolated nodes and ensure that the nodes can communicate with their CH with the shortest communication range to preserve the energy of the nodes. The objective is calculated as in Eq.(5.11) and Eq.(5.12).

$$dist(CH_i, MN_j)_{max} = max(\sqrt{(CH_i - MN_j)^2}) \tag{5.11}$$

$$dist(CH_i, MN_j)_{ave} = \frac{\sum_{i=1}^{n_{mn}}(dist(CH_i, MN_j)_{max})}{n_{mn}} \tag{5.12}$$

Where CH is the potential cluster heads at ith position, MN is the member nodes at jth position in the sensing area and n_{mn} is the number of member nodes.

Objective 3: The average residual energy of the candidate CHs, CH_E_{ave}. This objective ensures that the selected CH will possess higher residual energy compared to other nodes so that the node will not die off quickly by maintaining network stability for a longer period. The objective is calculated as in Eq.(5.13) and Eq.(5.14).

$$E_i = E_i - (E_{TX} + E_{RX}) \tag{5.13}$$

$$CH\_E_{ave} = \frac{\sum_{i=1}^{n_{ch}} E_i}{n_{ch}} \tag{5.14}$$

Where E_i is the residual energy of the candidate CH node, E_{TX} is the energy consumed during transmission of data based on the Eq.(5.2) from this chapter, E_{RX} is the energy consumed during reception of data based on the Eq.(5.3) from this chapter and n_{ch} is the number of potential cluster head nodes.

Objective 4: The candidate CH's maximum neighbour node degree, CH_ND_{max}. This objective is focused on the load balance of energy consumption in the clusters. Besides, it ensures that the CHs acquire an almost equal number of member nodes to avoid the quick death of CHs because of excessive data transmission from a large number of member nodes. The objective is calculated as in Eq.(5.15).

$$CH\_ND_{max} = max(CH_iND) \tag{5.15}$$

Where CH_iND is node degree of ith candidate CH in the sensing field.

Objective 5: The average isolated node probability, $CH_iINprob_{ave}$. This objective function is proposed to reduce the isolated node after CH selection, as much previous literature did not consider. This objective will ensure that optimal CHs are selected to cover the entire sensing region and avoid a node transferring data directly to BS, which will exhaust a lot of energy. For this objective, we consider a node is isolated to a CH at the ith position if its distance to the CH is more than the threshold distance, d0, as calculated in Eq.(5.1). The objective is calculated as in Eq.(5.16) and Eq.(5.17).

$$CH_iINprob = CH_iINprob + 1, \quad dist(CH_i, MN_j) > d0 \tag{5.16}$$

$$CH_iINprob_{ave} = \frac{\sum_{i=1}^{n_{ch}} CH_iINprob}{n_{ch}} \tag{5.17}$$

Where $CH_iINprob$ is the total isolated node for the ith CH, $dist(CH_i, MN_j)$ is the distance between the ith CH and the member nodes at jth position and n_{ch} is the number of potential cluster head nodes.

5.5 Cluster Head (CH) Selection, Cluster Formation and Multi-hop Routing

5.5.1 CH selection and Cluster formation

The main idea of clustering in WSN is to extend the lifetime of nodes with limited energy. Clustering is categorized into 2 phases which are (1) the CH selection phase and (2) the cluster formation phase. Some literature proposes to form clusters first before selecting a CH, but it is not the most efficient way as the optimal CH might not be selected, which, in return, will cause frequent re-clustering, which causes more overhead energy consumption. In the cluster head selection phase, the nodes near the optimal points (refer to Figure 5.4) are selected to be a cluster head, $CH_i, i = 1, 2, \cdots n$. Upon selecting the CH, the nodes that are not selected are labelled as member nodes, $MN_i, i = 1, 2, \cdots n$. WSN operation in a round system where in each round, the CH collects data from member nodes and transfers the data to BS. The process of CH selection by adaptive HSSOGA is depicted in the steps below.

Step 1: Initializing network parameters.

Initial the network parameters based on Table 5.2 below. Besides, initialize the proposed method's parameters as shown in Table 5.3 below. Every node that is deployed is given initial energy value, alive status and non-CH status.

Step 2: Initializing a population matrix, fitness calculation and population sorting.

The population is created based on a population matrix with the population parameter from Table 5.3, as shown in Eq.(5.18). The first and second column in the matrix defines the random positioning of the population with values between 0 to the area size, $[x_{min}, x_{max}]$, $[y_{min}, y_{max}]$ and third column defines a random threshold value, t with a value between 0 to 1. In every position of the population, it contains k number of positions, which enables the method to map the optimal solution, as shown in Figure 5.4.

$$pop_{1...n} = \begin{bmatrix} x_1^1 & y_2^1 & t_3^1 \\ x_1^2 & y_2^2 & t_3^2 \\ \vdots & \vdots & \vdots \\ x_1^k & y_2^k & t_3^k \end{bmatrix} \tag{5.18}$$

Where n is the total number of defined population (set to 100), and k is the maximum number of cluster heads allowed, which is 10% of the total number of deployed sensor nodes.

Step 3: Member Nodes joining clusters.

Some literature uses a few weighted calculations in the cluster formation phase to ensure the node joins the efficient CH (Rao et al., 2017). However, there is a possibility to select a CH that is far away from it and causes energy depletion quicker. As such, we propose the cluster is formed based on the shortest distance parameter. All member nodes calculate their distance to the selected CHs and join the cluster head that is nearest to it for data transfer based on Eq.(5.19) and Eq.(5.20). In this way, the energy dissipation of nodes over data communication is reduced.

$$DistToCH_{i,j} = \sqrt{(MN_i - CH_j)^2} \tag{5.19}$$

$$MN_{Clust_i} = j, \quad min(DistToCH_{i,j}) \tag{5.20}$$

Where $DistToCH_{i,j}$ is the distance of ith member node to jth CH node and MN_{Clust_i} is the cluster number that ith member node belongs to.

5.5.2 Proposed Clustering Technique

In LEACH, in every round, clustering is triggered to find new CH using a threshold, $T(n)$, and the CH's $T(n)$ are flagged as 0 so that it cannot act as a CH the following round to preserve the CH to last longer in the network. Threshold, $T(n)$ is calculated as in Eq.(5.21) (Yun et al., 2011):

$$T(n) = \begin{cases} \frac{P}{1-P\left(r mod \frac{1}{P}\right)}, & \text{if } n \in G \\ 0, & \text{otherwise} \end{cases} \tag{5.21}$$

Where P is the percentage of CH in the entire network, r is the round of CH selection, and G is the set of nodes that have not been elected as CHs in $1/P$ round (Sujee & Kannammal, 2015; Yun et al., 2011).

Re-clustering in LEACH occurs every round until all the nodes are dead in the network. Re-clustering is a phase where new CHs are selected, and new clusters are formed to preserve the network's energy and balance the workload. However, frequent re-clustering will cause an immoderate amount of control messages, increasing the network's energy consumption (Jin et al., 2011). Besides, node re-clustering causes frequent updates on the routing table, which might be limited to the nature of the limited memory size of the sensor nodes. These issues will lead to faster exhaustion of energy and memory of sensor nodes, making the entire network vulnerable.

To mitigate this issue, we simulated the clustering process in 2 different methods. In the first re-clustering technique, we enhance the LEACH clustering mechanism to reduce the re-clustering process. Clustering using this technique occurs every 10% drop in the CH's energy level compared to its previous energy level, ensuring that the nodes do not die off quickly and reducing the re-clustering process over time. Enhanced LEACH clustering mechanism is used because LEACH's clustering mechanism will cause a huge amount of time to re-cluster as the implementation of adaptive HSSOGA in clustering increases the time complexity of the method compared to LEACH. In the second clustering technique, we simulated the network to re-cluster once any of the nodes die, and this method is named Re-Clustering after a Node Dead (R-CND). This ensures that the network is stable for a longer period. However, the death of the first node might be quicker compared to the enhanced LEACH clustering technique that was explained before, but it will yield a longer functional period of the network. The results and discussion of using these techniques are explained in detail in Chapter 6 of this thesis. The re-clustering trigger, RC using technique 1, is depicted in Eq. (5.22), and the re-clustering trigger (RC) using technique two is depicted in Eq.(5.23).

$$RC = \begin{cases} 1, & \text{if } CH\_E_{i,j} \leq (CH\_E_{i,j-1} - 0.1) \\ 0, & \text{if } CH\_E_{i,j} > (CH\_E_{i,j-1} - 0.1) \end{cases} \tag{5.22}$$

$$RC = \begin{cases} 1, & \text{if } CH\_E_{i,j} \leq 0 \\ 0, & \text{if } CH\_E_{i,j} > 0 \end{cases} \tag{5.23}$$

Where $CH\_E_{i,j}$, is the energy level of ith CH in jth round, $CH\_E_{i,j-1}$, is the energy level of ith CH in its previous round, $j - 1$ and RC equals to 1 means enable clustering in the next round, and 0 means disable clustering on the next round.

5.5.3 Multi-hop Clustering

Routing is another crucial phase of WSN clustering, as the major focus of this research is the inter-cluster communication and efficiency of data transfer. Routing also contributes indirectly to energy consumption issues. For example, routing a node to send data over a long distance will exhaust the energy more compared shorter distance. So, proper routing is required to reduce the re-clustering process, which enhances the stability of the network. A multi-hop routing based on the shortest distance is implemented by giving importance to the problems faced by WSN and ensuring the quality of results in terms of network stability and inter-cluster communication efficiency. Since our BS is set to be out of sensing areas for easier accessibility, the crossover distance, d0, which is around 87m, is considered for transmission of data where CH that are located more than 87m of BS will tend to find the nearest distant CH to transfer data. Upon a CH receiving data from another CH, it aggregates and sends it to the BS. An example of multi-hop routing in first clustering is depicted in Figure 5.5.

5.6 Experimental Setup

The main purpose of this experiment is to ensure that the proposed metaheuristic method yields enhanced clustering by maintaining the stability of the network and efficient inter-cluster communications. The proposed adaptive HSSOGA clustering in WSN is evaluated to ensure its efficiency in both the enhanced LEACH clustering technique and the R-CND method, which will be discussed in Chapter 6. These evaluations are also extended to compare with the existing literature such as LEACH, HSAPSO (Shankar et al., 2016), HFAPSO (Pitchaimanickam & Murugaboopathi, 2020), and HGWOSFO (Lavanya & Shankar, 2021). Evaluation using the two clustering techniques will ensure that the proposed method can be adopted for different applications of clustering. The simulation of the clustering of WSN is programmed in MATLAB R2021a software on a computer

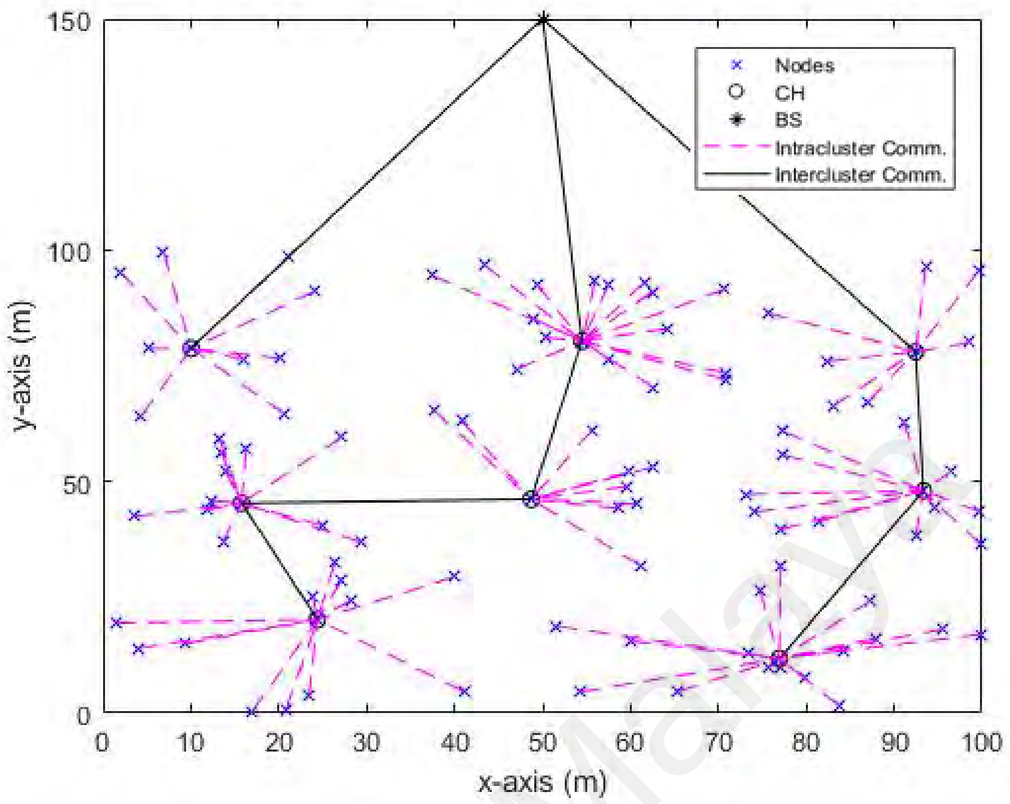

Figure 5.5: Implemented multi-hop routing

running Windows 10 Pro with 16GB DDR4 RAM and an AMD Ryzen 5 5600X 6-Core 3.7 GHz processor. MATLAB software is a very popular software used by many researchers because it is used for visualization of high-performance numerical optimization and computations (Qutaiba, 2012). Besides, MATLAB also integrates the Simulink program for enhanced simulation, analysis and visualization (https://www.mathworks.com/). Since clustering in WSN needs high visualization and flexibility (P. Gupta et al., 2014) MATLAB is used compared to many other network simulators such as NS-2 and NS-3.

WSN implementation is done in applications such as agricultural networks (Aquino Santos et al., 2011), smart home networks (Bamimore & Ajagbe, 2020), military communication (S. H. Lee et al., 2009), and environmental sensing systems (Fascista, 2022). Some are small-scale systems, and some are large-scale systems. So, from the survey of many literatures in Chapter 2, the standard parameter setting for WSN simulation is selected for the simulation environment as depicted in Table 5.2 below.

Table 5.2: Standard WSN simulation parameters

Parameters	Value
Area	100m x 100m
Base Station Location	(50, 150)
Number of Nodes deployed	100
Sensor Initial Energy	1J
Packets size	4000 bits

The parameters setting used by adaptive HSSOGA, HFAPSO, HSAPSO and HGWOSFO for selecting optimal CH are listed in the Table 5.3 below:

Table 5.3: List of parameters of adaptive HSSOGA, HFAPSO, HSAPSO, and HGWOSFO

Parameters	Values
HSSOGA/aHSSOGA	
Velocity damping factor (D)*	Changed linearly (Initially = 0.1)
Temperature	Rand (35.5, 38.5)
pH	Rand (7, 14)
Crossover Percentage (pc)*	Changed adaptively (Initially = 0.7)
Mutation Percentage (pm)*	Changed adaptively (Initially = 0.3)
Mutation Rate (mu)	0.02
Selection Pressure $(beta)$	8
HFAPSO	
Light Absorption Coefficient (γ)	1
Attraction Coefficient Base Value $(\beta 0)$	2
Mutation Coefficient (α)	0.2
Mutation Coefficient Damping Ratio (α_{damp})	0.98
Uniform Mutation Range (δ)	5
Inertia Weight Damping Ratio $(wdamp)$	0.99
$c1$	1.5
$c2$	1.5
HSAPSO	
bw	0.2
Harmony Memory Considering Rate $(HMCR)$	0.95
Pitch Adjustment Rate (PAR)	0.3
Inertia Weight Damping Ratio $(wdamp)$	0.99
$c1$	1.5
$c2$	1.5

Continued on next page

Table 5.3, continued

Parameters	Values
HGWOSFO	
Pollination Rate ($polli$)	0.05
Mortality Rate ($mort$)	0.1
$c1, c2, c3$	2 * Rand(0,1)
a	Linearly decreasing from 2 to 0

$*$. For the non-adaptive version of HSSOGA, the values for D, pc and pm are set to initial values of 0.1, 0.7 and 0.3, respectively.

5.7 Chapter Summary

This chapter has discussed the advantages of having adaptive exploration and exploitation in real-world optimization scenarios, which are focused on Wireless Sensor Networks (WSNs). From surveying the literature, the research gap on the hybrid metaheuristic method is outlined, where adaptive exploration and exploitation will tune the metaheuristic method to behave according to the real-world scenario to provide better optimal solutions. In the case of WSN, CH selection is a vital phase of clustering in WSN as it determines the best node to become CH for an enhanced network. The proposed metaheuristic method in Chapter 4 is enhanced to cater for the optimization in WSN by enabling adaptive tuning of crossover and mutation operators of GA and controlling the velocity of SSO in HSSOGA. This ensures that at a particular point in time, whether exploration or exploitation is to be given attention. The process flow and steps of the method are outlined in detail for better understanding. A set of objective functions are needed to ensure that the proposed adaptive HSSOGA can select the optimal CH to mitigate the network hole problem and isolated node problem. Given the mentioned problems, a set of new objective functions is proposed to reduce the isolated node problem by ensuring the proposed method will be optimized to select the best CH. So, five objective functions are discussed in this chapter which are (1) the average distance between candidate CHs and other candidate CHs, (2) the average distance between the candidate CHs and member nodes in a cluster, (3) the average residual energy of the candidate CHs, (4) candidate CH's maximum neighbour node degree and (5) average isolated node probability. Moreover, the cluster formation and routing phase are discussed, where clusters are formed using the shortest distance measure for member nodes to join the nearest CH to form clusters. On the other hand, a multi-hop routing protocol is applied in this experiment to ensure that the energy consumption is reduced for a better network lifetime. The experimental set-ups and assumption of the WSN simulated are also outlined in detail, ensuring that the proposed adaptive HSSOGA are evaluated using the two proposed clustering techniques for performance validity.

CHAPTER 6: EVALUATION AND VERIFICATION OF ADAPTIVE HYBRID METAHEURISTIC METHOD IN WSN CLUSTERING

6.1 Introduction

Upon looking at the experimental set-up and WSN environment parameters settings in the previous chapter, this chapter discusses the performance metrics used to analyze the simulation results as well as provides valuable discussions based on the results to ensure the stated objectives are met. This chapter also gives a detailed discussion of the pros and cons of the proposed academic HSSOGA in optimizing WSN based on the obtained results. The evaluation is focused on two categories which are ensuring the stability of the network in terms of network lifetime and energy dissipation of the nodes and inter-cluster communication efficiency in terms of network throughput and packet transfer rate of the nodes. The remainder of this chapter is as follows: Firstly, the performance metrics of this experiment in terms of network stability and inter-cluster communication efficiency are described in section 6.2. Section 6.3 shows performance metrics results based on two clustering techniques using the proposed academic HSSOGA and comparing it to the existing state-of-art in clustered WSN. Section 6.4 outlines a detailed analysis and discussion of the obtained results. Finally, in section 6.5, a brief chapter summary is given.

6.2 Performance Metrics

A stable cluster is a cluster that has minimal re-clustering, which limits the energy consumption of the network (Ayyub et al., 2022). Besides, the stability of a network is also determined by the network lifetime and energy consumption of a network. On the other hand, communication in a network is vital as it ensures the information is passed to the BS for analysis of the environment, medical status and disaster management. Maximizing communication efficiency should be the number 1 priority in any network scenario. As such, this work intends to ensure. So, the performance metrics used to measure the overall network stability and Inter-cluster communication efficiency are described below:

6.2.1 Average Residual Energy

The average residual energy of a network is an important metric as it can show the efficiency of the proposed method to select the optimal CHs. The average residual energy for each round (E_r) of the network can be calculated as in Eq.(6.1) below.

$$E_r = \frac{\sum_{i=1}^{n} E_i}{n_{alive}} \tag{6.1}$$

Where E_r is the average residual energy in round r, E_i is the residual energy of node i, and n_{alive} is the total number of alive nodes.

6.2.2 Network Lifetime

Network lifetime is determined by the number of nodes alive compared to the number of rounds the network was functional. As such, the values of First Node Dead (FND), Half Node Dead (HND) and Last Node Dead (LND) are evaluated. The FND is the round where one of the nodes dies off first from battery energy exhaustion in the network, HND is the round where half (50%) of the node in the network exhausts its battery energy completely, and LND is the round it takes for all (100%) the nodes to drain its battery energy. The longer time taken for FND is said that the network is more stable as a node death will disrupt the information flow and network coverage (Ayyub et al., 2022).

6.2.3 Number of re-clustering occurrence

Re-clustering is deemed to cause extra overhead and high energy consumption (Alomari et al., 2022). So, to reduce the re-clustering occurrence, two clustering techniques were introduced, as explained in Chapter 5, section 5.5.2. The number of re-clustering occurrences until LND is evaluated with some existing state-of-art to ensure reduced energy consumption.

6.2.4 Total Data Delivery

The total data delivery shows the total bits of data successfully delivered over the total rounds that the network is functional, with at least one node being alive. This ensures that BS can collect more information for processing. Higher data delivery shows better communication efficiency of the network. The total data delivery for every round (TDD_r) is calculated as in Eq.(6.2).

$$TDD_r = TDD_{r-1} + \sum_{i=1}^{n} P_{Delivered} \tag{6.2}$$

Where $P_{Delivered}$ is the total amount of data delivered in bits to the base station in rth round.

6.2.5 Network throughput

Network throughput ($Throughput_r$) shows the number of data being transferred over the total time it takes to complete the round. The higher the network throughput, the better the network's communication as more data is sent over a short period. These metrics can be calculated as in Eq.(6.3) below:

$$Throughput_r = \frac{TotalP_{sent}}{TT_r} \tag{6.3}$$

Where $TotalP_{sent}$ is the total data in bits sent in rth round, and TT_r is the time taken for rth round to be completed.

6.2.6 End-to-End Delay

End-to-end delay in a wireless network shows the time for packets to reach the destination (BS). So, end-to-end delay for every round (EED_r) should be minimized to ensure efficient data transfer. The routing path of CHs also plays an important role as longer multi-path routing takes more time, causing an increase in end-to-end delay. Moreover, having an optimal CH will also ensure efficient multi-path routing. The End-to-end delay performance metric is calculated as in Eq.(6.4) below:

$$EED_r = \frac{\sum_{i=1}^{P_{received(i)}} (T_{received(i)} - T_{sent(i)})}{P_{received}} \tag{6.4}$$

Where $P_{received(i)}$ is the total number of received packets by the base station from node i in rth round, $T_{received(i)}$ and $T_{sent(i)}$ are the time taken for the packet to be received by the base station and time taken for the packets to be sent by the node i respectively.

6.3 Results

The results show the performance of proposed HSSOGA and aHSSOGA in terms of network stability and inter-cluster communication efficiency, which comprises metrics such as network lifetime, average residual energy, re-cluster occurrence, total packet delivery, network throughput and end-to-end delay metrics. These performances are compared with some existing clustering metaheuristic methods called LEACH, HSAPSO (Shankar et al., 2016), HFAPSO (Pitchaimanickam & Murugaboopathi, 2020), and HGWOSFO (Lavanya & Shankar, 2021).

6.3.1 Comparison under clustering method 1 (Enhanced LEACH Clustering)

The results are depicted in Figures 6.1, 6.2, 6.3, 6.4, 6.5 and 6.6, as well as in Tables 6.1, 6.2, 6.3, 6.4, 6.5 and 6.6, where the best result is shown in bold text.

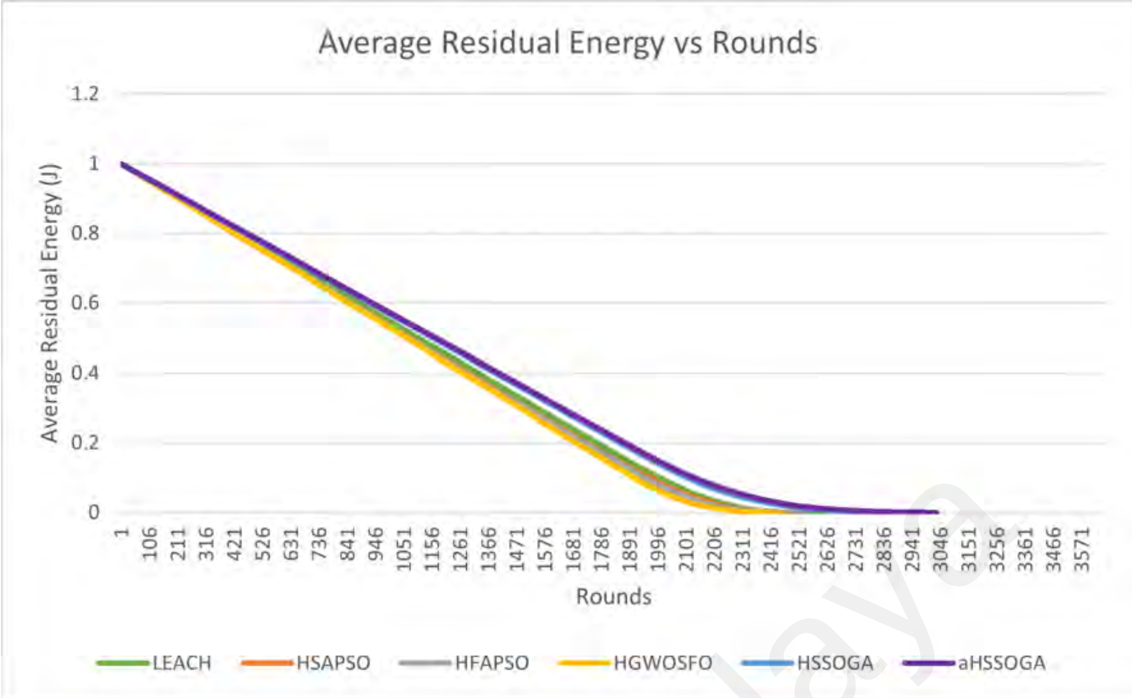

Figure 6.1: Average Residual Energy over Number of Rounds using Enhanced LEACH Clustering

The figure above shows the comparison of the average residual energy of the network after the CH selection and cluster formation process using the enhanced LEACH method. At round 1000, the drop in average residual energy of the network can be seen clearly from the figure where LEACH was able to show the average residual energy of 0.549J compared to HSAPSO, HFAPSO and HGWOSFO, which recorded average residual energy of 0.534J, 0.533J, 0.531J respectively. However, our proposed HSSOGA method and its modified version of aHSSOGA manage to record 0.570J and 0.573J of average residual energy at the 1000th round. The difference in the value is caused by the additional objective function that is introduced to our proposed method for clustering. HSAPSO, HFAPSO and HGWOSFO use only energy and CH distance metrics as the objective function according to its literature (Lavanya & Shankar, 2021; Pitchaimanickam & Murugaboopathi, 2020; Shankar et al., 2016) respectively. The network achieved 50% remaining energy in round 1106 for LEACH, round 1072 for HSAPSO, round 1070 for HFAPSO, round 1064 for HGWOSFO and round 1162 for HSSOGA. Adaptive HSSOGA managed to record half the remaining energy of the network on round 1171, which is 5.55% better compared to LEACH, 8.45% better compared to HSAPSO, 8.63% better than HFAPSO, 9.12% better than HGWOSFO and 0.77% better than its conventional HSSOGA method. Moreover, the adaptive HSSOGA had higher residual energy than other methods from round 5 to the end of the network lifetime, which means the network's energy consumption was reduced. This is because the adaptive change of exploration and exploitation in HSSOGA enables it to select the most efficient CH and form clusters efficiently so that energy is well-conserved.

Table 6.1: Statistical analysis of average residual energy metric using "One-way ANOVA (Tukey's test)" between aHSSOGA and the other existing methods using Enhanced LEACH Clustering

Algorithm (I)	Algorithm (J)	Mean Difference (I-J)	p-Value (Sig.)
aHSSOGA	LEACH	**-0.0344***	**0.001***
	HSAPSO	**-0.0447***	**< 0.001***
	HFAPSO	**-0.0340***	**0.001***
	HGWOSFO	**-0.0437***	**< 0.001***
	HSSOGA	**-0.0250***	**0.032***
*. The mean difference is significant at the 0.05 level.			

From Table 6.1, it can be seen that the aHSSOGA outperformed LEACH, HSAPSO, HFAPSO, HGWOSFO and its conventional HSSOGA by obtaining the significance value for the average residual energy metric, which fulfils the statement in Chapter 4, where HSSOGA is well suited for a real-world situation such as this WSN environment based on the unimodal and multimodal experiments. From this analysis, we can conclude that the proposed adaptive method reduces energy consumption and ensures that the residual energy is preserved to prolong the lifetime of the network.

A detailed analysis of the network lifetime can be derived from Table 6.2 and Figure 6.2 below.

From the results above, it can be seen that HFAPSO took longer rounds for its first node to die, which is at round 1904, compared to aHSSOGA recorded 25 rounds before

Table 6.2: Comparison of FND, HND and LND values using Enhanced LEACH Clustering

Algorithm	FND	HND	LND
LEACH	1779	2209	2619
HSAPSO	1821	2194	2490
HFAPSO	**1904**	2154	2541
HGWOSFO	1788	2105	2453
HSSOGA	1844	2290	2820
aHSSOGA	1879	**2348**	**3038**

at round 1879. However, aHSSOGA outperformed all the existing methods in Half Node Dead (HND) and Last Node Dead (LND), which shows a longer network lifetime. The visualization of the total number of nodes alive along the iterations is depicted in Figure 2 below. The steady drop in the number of alive nodes using aHSSOGA for CH selection ensures that CH preserves the energy efficiently by selecting the node with higher residual energy to become candidate CH. Adaptive HSSOGA has a better network lifetime by 13.79%, 18.04%, 17.58%, 19.26% and 7.18% compared to LEACH, HSAPSO, HFAPSO, HGWOSFO and conventional HSSOGA respectively. Besides, the LEACH method provides a better network lifetime compared to some existing methods such as HFAPSO, HGWOSFO and HSAPSO. This can also be caused by the objective functions used by the method's literature as, for the second time, the results obtained prove that the proposed refined objective function in this thesis yields a better WSN clustering in terms of network lifetime.

To reduce the re-clustering process to reduce the energy overhead cost (G. Gupta & Younis, 2003) and maintain network stability, this thesis introduces an enhanced LEACH clustering method discussed in Chapter 5, section 5.1. The total re-clustering process that takes place until all nodes' dies are analyzed in Table 6.3 below.

From the results, it can be analyzed that the proposed aHSSOGA had the lowest re-clustering calls over the total number of rounds, making it a stable network. It can

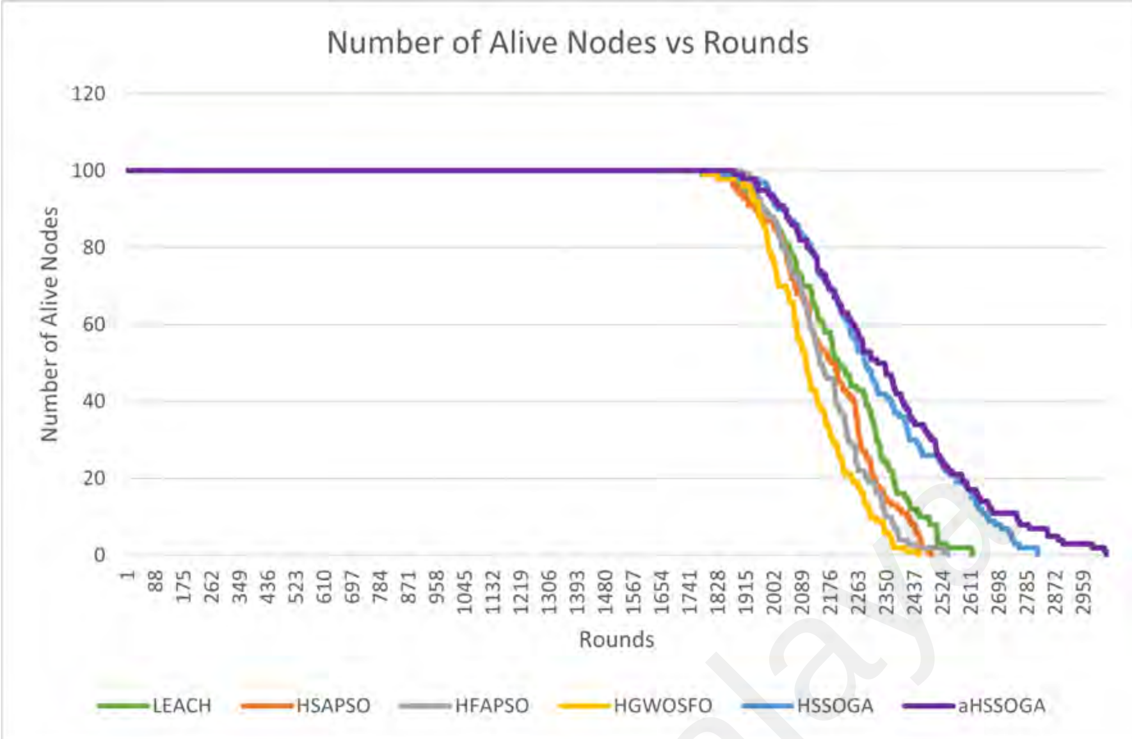

Figure 6.2: Total Operating Nodes over Number of Rounds using Enhanced LEACH Clustering

Table 6.3: Comparison of total re-clustering values using Enhanced LEACH Clustering

Algorithm	**Re-Clustering times**
LEACH	2618
HFAPSO	244
HGWOSFO	288
HSSOGA	175
SSOGA	**169**

also be learnt that aHSSOGA only performs a 5.56% re-clustering process from the total rounds of the operating network, which means it drastically reduces the overhead energy cost, as proven by the Tables and Figures above. On the other hand, LEACH's clustering method clusters every functional round of the network, increasing the processing time to cluster and degrading the clustering process due to the transmission of many broadcast packets during the process (Jung et al., 2011).

In this thesis, communication efficiency within clustered WSNs is given the same priority attention as the stability of the network. Firstly, the total packets delivered metric is evaluated to ensure higher efficiency of data transfer to BS for further processing, as the results from the simulation are depicted in Figure 6.3 below.

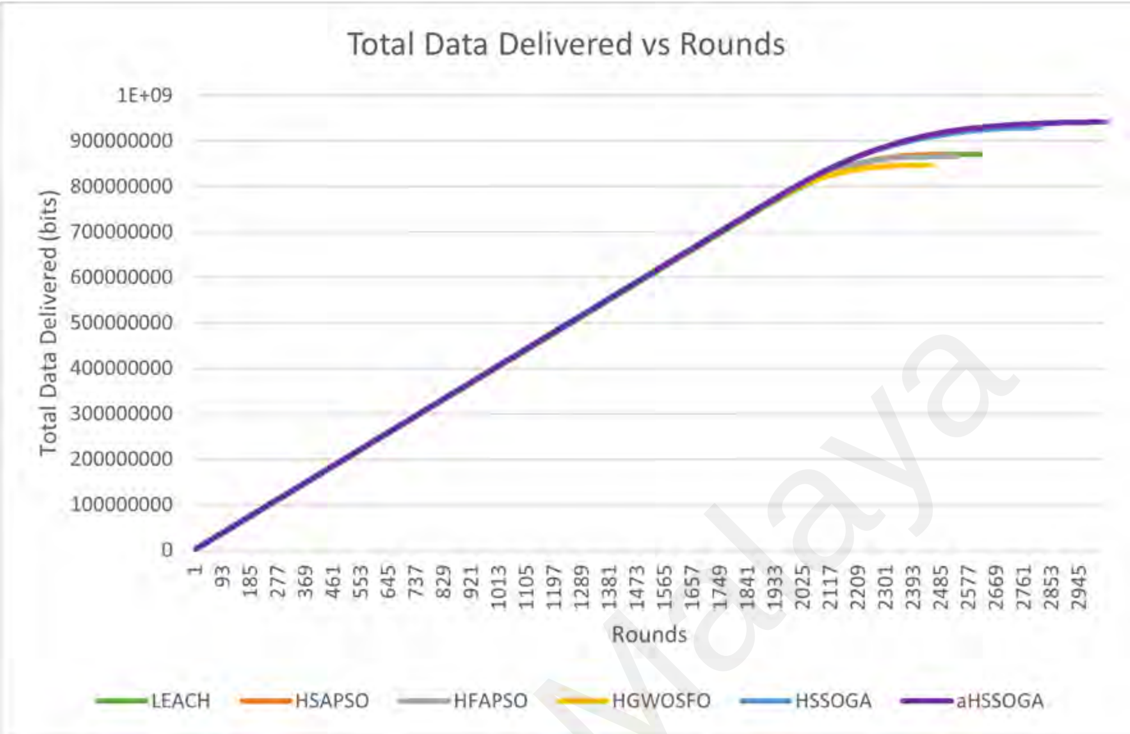

Figure 6.3: Total Packet Delivery over Number of Rounds using Enhanced LEACH Clustering

The figure above shows that the same number of data were being delivered to BS until round 1788. This is because the earliest first node dead in the network is from using HGWOSFO for CH selection. So, when a node dies, it affects the communication efficiency of a network. Moreover, HSSOGA and aHSSOGA show a good data delivery rate as the network lasts longer and the nodes can transfer the data efficiently. The total data transferred by LEACH, HSAPSO, HFAPSO, HGWOSFO, HSSOGA and aHSSOGA until the last node dead are $1.65 * 10^{11}$ bytes, $1.52 * 10^{11}$ bytes, $1.57 * 10^{11}$ bytes, $1.47 * 10^{11}$ bytes, $1.91 * 10^{11}$ bytes, and $2.17 * 10^{11}$ bytes respectively. From these results, we can conclude that aHSSOGA performance on total data delivery is 23.96% better than LEACH, 29.95% better than HSAPSO, 27.65% better than HFAPSO, 32.36% better than HGWOSFO and 11.98% better than HSSOGA which makes it the best method for efficient data delivery.

Table 6.4: Statistical analysis of total data delivered metric using "One-way ANOVA (Tukey's test)" between aHSSOGA and the other existing methods using Enhanced LEACH Clustering

Algorithm (I)	Algorithm (J)	Mean Difference (I-J)	p-Value (Sig.)
aHSSOGA	LEACH	**66783003.72***	**< 0.001***
	HSAPSO	**83637632.86***	**< 0.001***
	HFAPSO	**76076316.17***	**< 0.001***
	HGWOSFO	**91698142.51***	**< 0.001***
	HSSOGA	**28947931.26***	**0.001***
*. The mean difference is significant at the 0.05 level.			

The table above shows that using aHSSOGA in CH selection using the enhanced LEACH clustering outperforms significantly compared to LEACH, HSAPSO, HFAPSO, HGWOSFO and HSSOGA. This shows that the proposed aHSSOGA enables a longer lifetime of the network that contributes to higher data transfer to BS.

Network throughput ensures that the data are delivered quickly, and it is an important metric to be analyzed for real-time application for communication efficiency. The network throughput of the network for every round is depicted in Figure 6.4 below.

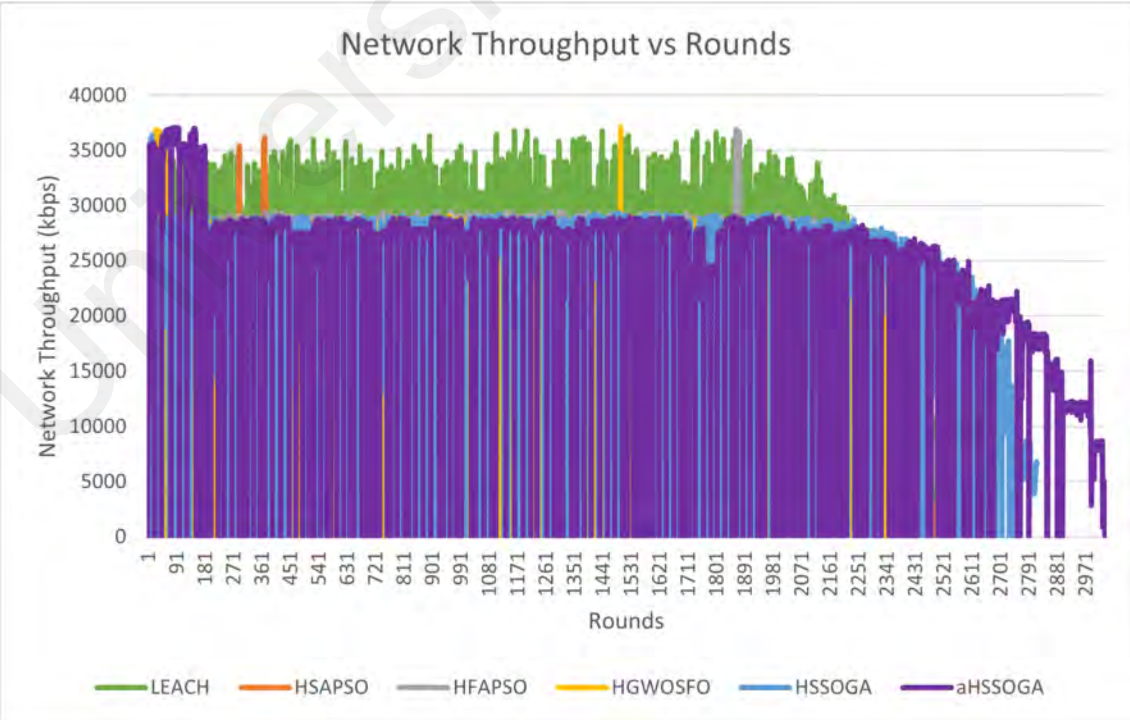

Figure 6.4: Network Throughput over Number of Rounds using Enhanced LEACH Clustering

From the evaluation, LEACH yielded a better throughput compared to other metaheuristic methods. LEACH obtained an average throughput of 24371.63 kbps while HSAPSO, HFAPSO, HGWOSFO, HSSOGA and aHSSOGA obtained an average throughput of 23003.65 kbps, 22889.87 kbps, 21111.69 kbps, 23326.84 kbps and 24647.32 kbps respectively. From the averages, aHSSOGA yielded better average throughput compared to LEACH. Even though LEACH had a good network throughput in the beginning rounds, its network throughput deteriorated towards the end of the network lifetime. This is because LEACH uses direct data transmission from CH to BS without multi-hop routing, ensuring data are transmitted directly without interruption. Meanwhile, the HSSOGA and aHSSOGA methods use multi-hop transmission that reduces the network throughput slightly but greatly reduces the energy consumption of nodes over transmission, as the more the transmission distance, the higher the energy consumption. The last 100 rounds of LEACH and aHSSOGA method are visualized in Figure 6.5.

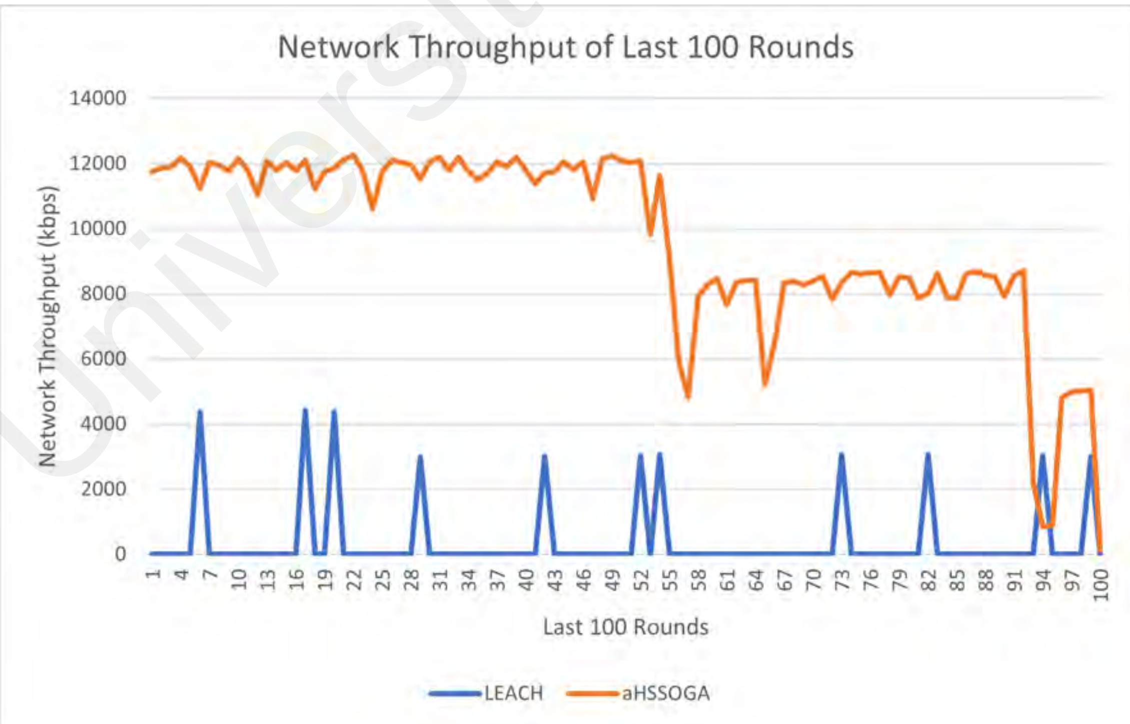

Figure 6.5: Network Throughput of LEACH and aHSSOGA in the last 100 rounds using Enhanced LEACH Clustering

From the figure above, it can be described that LEACH recorded very low network throughput towards the end of the network lifetime, or none (0), compared to aHSSOGA, which recorded a higher network throughput even towards the end. So, these results show that the LEACH method faces an isolated node problem that cannot send data directly to BS or a network hole problem where no nodes near BS can act as a CH to transmit the data to BS. However, the drop in the last 55 rounds of proposed aHSSOGA's network throughput is caused by the nodes dying where the packets transmitted over time are reduced. It can be concluded that the proposed aHSSOGA has ensured the objective of reducing isolated node problems and network hole problems is achieved by having adaptive exploration and exploitation ability as well as improved objective function using the enhanced LEACH clustering method. The network throughput significance of the proposed aHSSOGA against the other existing methods using enhanced LEACH clustering is depicted in Table 6.5 below.

Table 6.5: Statistical analysis of network throughput metric using "One-way ANOVA (Tukey's test)" between aHSSOGA and the other existing methods using Enhanced LEACH Clustering

Algorithm (I)	Algorithm (J)	Mean Difference (I-J)	p-Value (Sig.)
aHSSOGA	LEACH	275.686	0.831
	HSAPSO	**1643.668***	**< 0.001***
	HFAPSO	**1757.448***	**< 0.001***
	HGWOSFO	**3535.629***	**< 0.001***
	HSSOGA	**1320.476***	**< 0.001***
*. The mean difference is significant at the 0.05 level.			

The proposed aHSSOGA outperformed HSAPSO, HFAPSO, HGWOSFO and HSSOGA significantly, with a significance level 0.05. It did not provide significant performance to LEACH because of its better network throughput in the beginning rounds because of its single-hop transmission compared to the other existing metaheuristic methods. It can be concluded that aHSSOGA is the best metaheuristic method among the other metaheuristic method in creating clusters using enhanced LEACH technique.

End-to-end delay is closely related to the network throughput, but it allows an evaluation of the efficiency of BS receiving the data in the particular round in a short period, as the results are depicted in Figure 6.6 below.

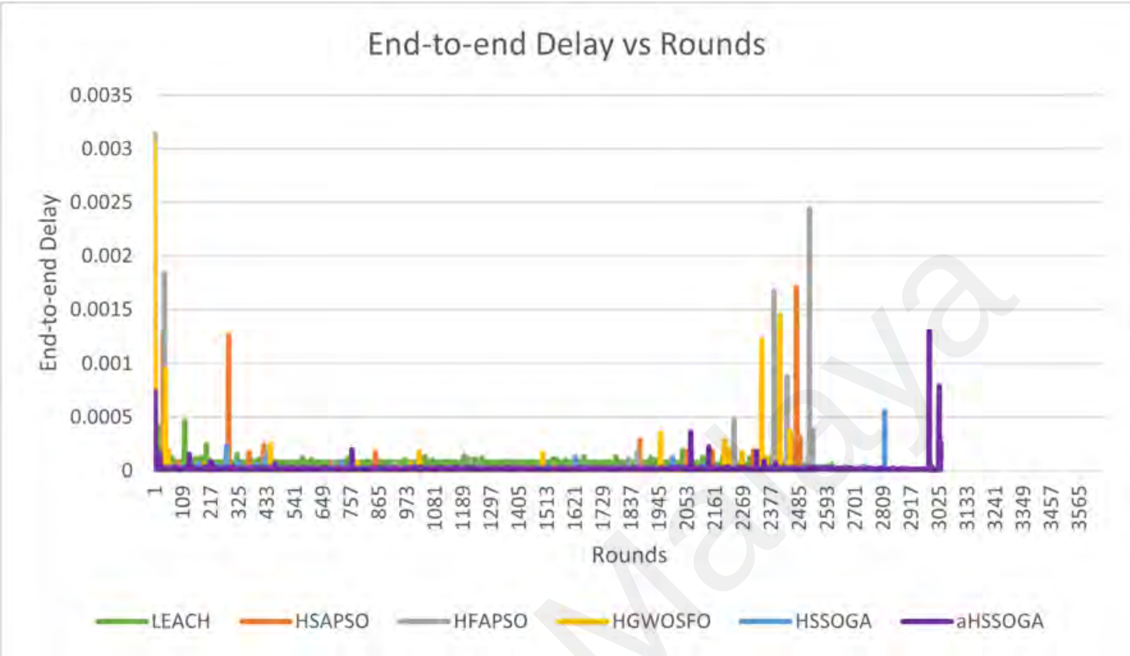

Figure 6.6: End-to-end Delay over Number of Rounds using Enhanced LEACH Clustering

The end-to-end data transfer delay for all the metaheuristic methods initially and towards the end. Initially, the routing table creation and learning of routes take additional time before the data is delivered to BS. On the other hand, toward the end of the network lifetime, many nodes have died and caused the remaining few nodes to send data to a far CH or with a longer distance to BS which also causes a spike in the end-to-end delay. The average end-to-end delay of LEACH, HSAPSO, HFAPSO, HGWOSFO, HSSOGA and aHSSOGA are 0.072ms, 0.019ms, 0.020ms, 0.020ms, 0.020ms, 0.018ms and 0.018ms respectively. HSSOGA and aHSSOGA recorded better averages compared to other metaheuristic methods that show the optimal CHs are selected for efficient communication of nodes to CH and CH to BS. The significance of aHSSOGA towards the other existing clustering method is shown in Table 6.6 below.

Table 6.6: Statistical analysis of end-to-end delay metric using "One-way ANOVA (Tukey's test)" between aHSSOGA and the other existing methods using Enhanced LEACH Clustering

Algorithm (I)	Algorithm (J)	Mean Difference (I-J)	p-Value (Sig.)
aHSSOGA	LEACH	**-5.383E-05***	**< 0.001***
	HSAPSO	-1.583E-06	0.960
	HFAPSO	-2.240E-06	0.838
	HGWOSFO	-2.095E-06	0.878
	HSSOGA	-2.778E-07	1.000

*. The mean difference is significant at the 0.05 level.

Adaptive HSSOGA only manage to show significant results towards LEACH for end-to-end delay metric because only LEACH uses single hop transmission that increase the overall end-to -end delay of data transmission compared to the other metaheuristic methods that uses multi-hop transmission. It can be concluded that even though aHSSOGA did not show significance performance compared to other metaheuristic methods, it outperformed the other metaheuristic method by having a lower end-to-end delay.

6.3.2 Comparison under clustering method 2 (Re-Clustering after a Node Dead (R-CND))

In this comparison the LEACH method is excluded because comparing LEACH with newly proposed clustering technique (R-CND) is not comparable in terms of the metrics stated in this chapter section 6.2. So, this subsection will compare the results of 5 metaheuristic method called, HSAPSO, HFAPSO, HGWOSFO, HSSOGA and proposed aHSSOGA. The results are depicted in Figure 6.7, 6.8, 6.9, 6.10, 6.11 and 6.12 as well as in Table 6.7, 6.8, 6.9, 6.10, 6.11, 6.12 and 6.13 where the best result is shown in bold text.

The figure above shows that the average residual energy for all the methods used for CH selection where aHSSOGA has a higher residual energy at the beginning of the network rounds and after 2300th round. At 2300th round aHSSOGA recorded an average residual energy of 0.165J compared to HSAPSO that recorded 0.148J, HFAPSO that recorded 0.147J, HGWOSFO that recorded 0.158J and HSSOGA that recorded 0.163J. Moreover,

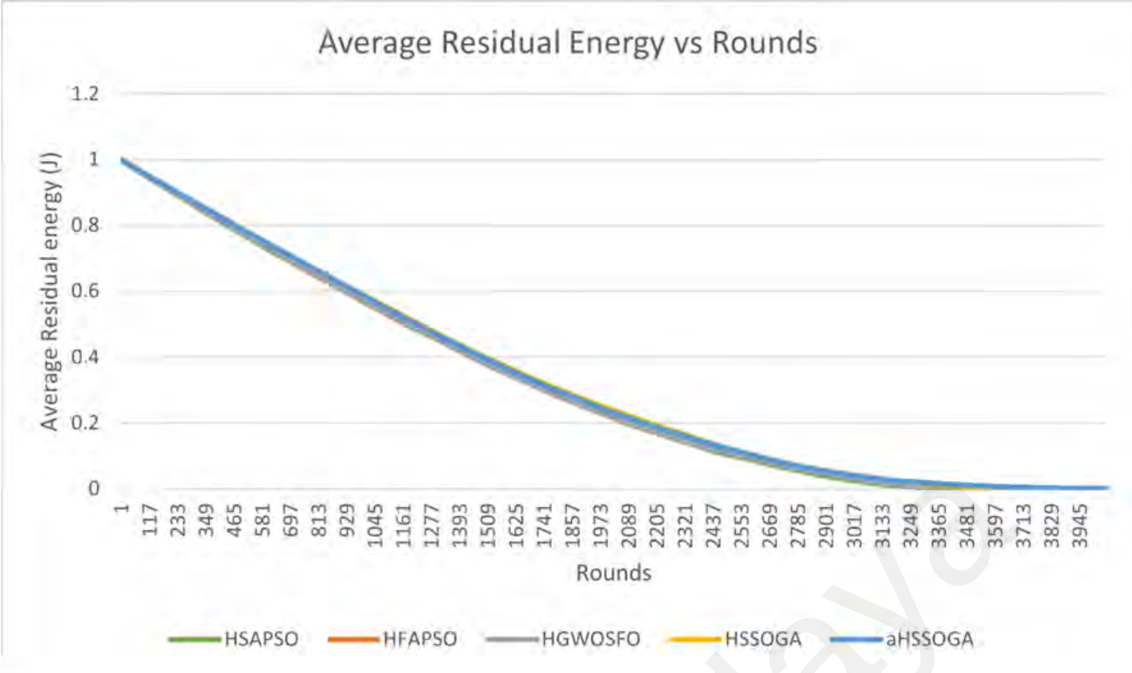

Figure 6.7: Average Residual Energy over Number of Rounds using Re-Clustering after a Node Dead (R-CND)

the network had 50% of energy at round 1171 for HSAPSO, round 1177 for HFAPSO, round 1177 for HGWOSFO, round 1224 for HSSOGA and round 1216 for aHSSOGA. This results shows that the non-modified HSSOGA performs well by selecting better CH in mid network cycles using R-CND clustering method. However, aHSSOGA preserves more energy towards the end of network cycle with lesser number of alive nodes. To ensure the significance of the performance of aHSSOGA on this metric is evaluated using the One-way ANOVA (Tukey's test) evaluation as depicted in Table 6.7 below.

Table 6.7: Statistical analysis of average residual energy metric using "One-way ANOVA (Tukey's test)" between aHSSOGA and the other existing methods using Re-Clustering after a Node Dead (R-CND)

Algorithm (I)	Algorithm (J)	Mean Difference (I-J)	p-Value (Sig.)
aHSSOGA	HSAPSO	**-0.047***	**< 0.001***
	HFAPSO	**-0.039***	**< 0.001***
	HGWOSFO	**-0.023***	**0.010***
	HSSOGA	**-0.024***	**0.004***
*. The mean difference is significant at the 0.05 level.			

The statistical analysis shows that the proposed aHSSOGA has significantly outperformed the other existing metaheuristic methods with a significant value lesser than 0.05. Even though the results from Figure 6.7 shows the recorded average residual energy have slight difference, HSSOGA outperformed the other methods in the start of the network cycle and towards the end of network cycle which shows clearly that aHSSOGA selects optimal CH in vision of prolonging the network lifetime.

The network lifetime prolonging can be analyzed further using the results obtained in Table 6.8 and Figure 6.8 below.

Table 6.8: Comparison of FND, HND and LND values using Re-Clustering after a Node Dead (R-CND)

Algorithm	**FND**	**HND**	**LND**
HSAPSO	79	2326	3416
HFAPSO	84	2224	3542
HGWOSFO	89	2164	3664
HSSOGA	129	**2552**	3735
aHSSOGA	**133**	2484	**4059**

Adaptive HSSOGA recorded the longest round to have a node to die first which shows that aHSSOGA managed to find optimal CHs at the beginning of clustering. However, the conventional HSSOGA performed well in the mid of network cycle as aHSSOGA focuses on preserving the node's energy towards the end of the network cycle to ensure longevity of the functional network. Adaptive HSSOGA has a better network lifetime where it performs 15.84% better than HSAPSO, 12.74% better than HFAPSO, 9.73% better than HGWOSFO and 7.98% better than its conventional HSSOGA. Both aHSSOGA and HSSOGA shows better results in all FND, HND and LND. This is because of its improved objective function that involves isolated node probability and neighbor node degree compared to the objective functions used by the method HSAPSO, HFAPSO and HGWOSFO as discussed in Chapter 5 section 5.4 of this thesis. Figure 6.8 shows a visualization of the number of operating nodes in each round of the network.

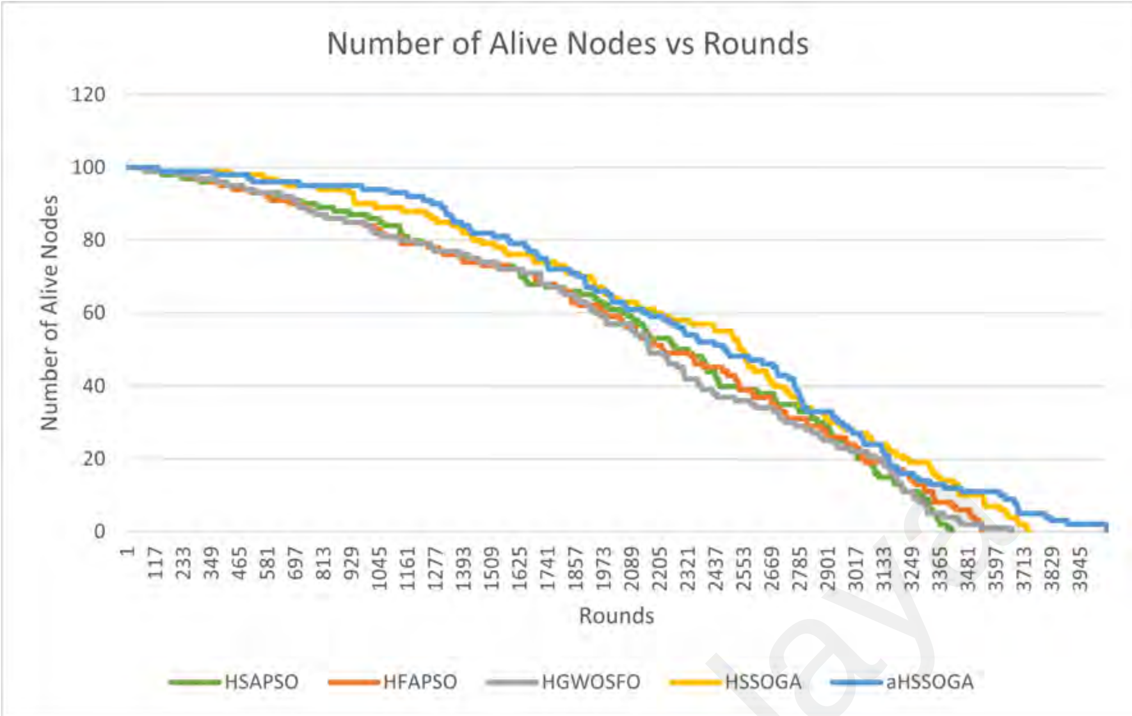

Figure 6.8: Total Operating Nodes over Number of Rounds using Re-Clustering after a Node Dead (R-CND)

Adaptive HSSOGA manage to have longer lifetime after only having 10 alive nodes compared to HSAPSO, HFAPSO, HGWOSFO and HSSOGA. This shows that aHSSOGA ensures that the last few nodes are not far away (isolated) from BS which makes the energy preservation better and fulfills the objective of reducing isolated node problem and hotspot problem.

Table 6.9: Comparison of total re-clustering values using Re-Clustering after a Node Dead (R-CND)

Algorithm	Re-Clustering times
HSAPSO	50
HFAPSO	49
HGWOSFO	58
HSSOGA	49
aHSSOGA	**45**

From the results obtained above, aHSSOGA managed to record the lowest re-clustering round compared to the other existing algorithms of clustering. This shows that aHSSOGA has chosen optimal CHs with a higher residual energy which reduces the re-clustering occurrence. Re-clustering after a Node Dead (R-CND) is deemed to be a good clustering method as it dramatically reduces the frequent re-clustering occurrence to minimize the overhead energy cost where aHSSOGA only triggered re-clustering for 1.11% times of its total network operating rounds. On the other hand, HSAPSO, HFAPSO, HGWOSFO and HSSOGA only re-clustered 1.46%, 1.38%, 1.58% and 1.31% of the total rounds of operational network respectively.

The inter-cluster communication efficiency using R-CND clustering method are analyzed below to ensure communication performance of proposed aHSSOGA is significant. The total data delivered to BS in every operational round is evaluated as Figure 6.9 below.

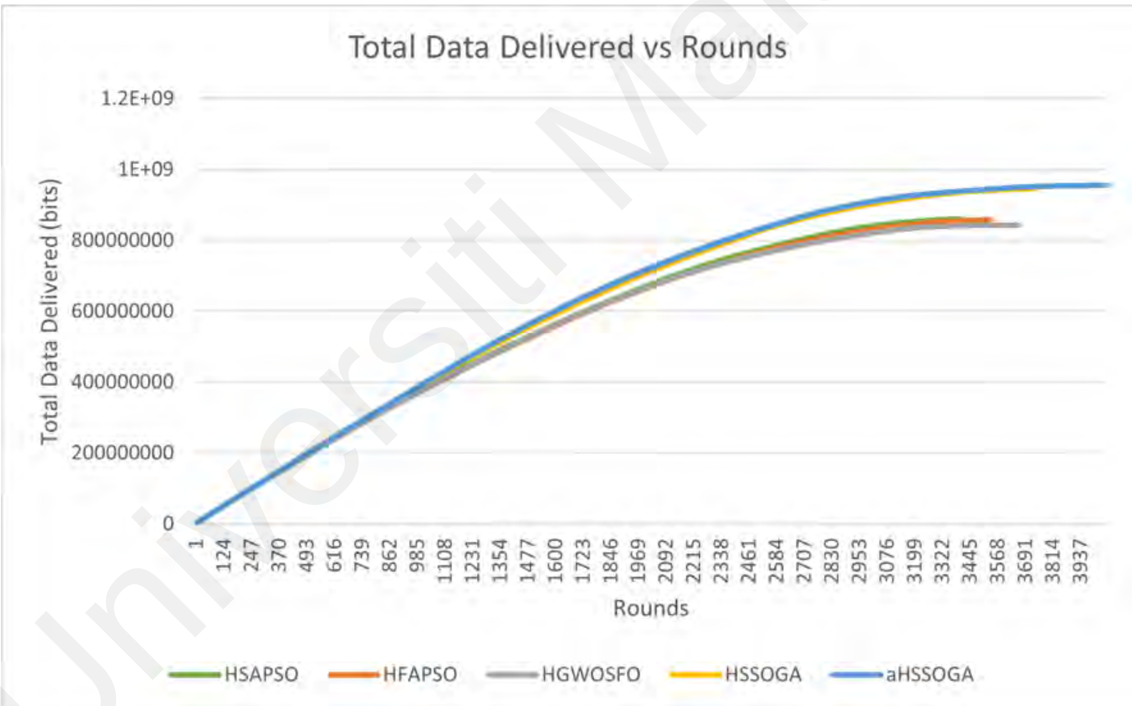

Figure 6.9: Total Packet Delivery over Number of Rounds using Re-Clustering after a Node Dead (R-CND)

From the results, ahSSOGA and HSSOGA have delivered a higher number of data compared to HSAPSO, HFAPSO and HGWOSFO which shows an efficient data communication. This is because of the longevity of the network lifetime provided by these methods. At round 2000 of the network which is almost the halfway mark for the total rounds recorded by aHSSOGA clustered network, aHSSOGA recorded $8.94 * 10^7$ bytes compared to HFAPSO HSAPSO, HGWOSFO and HSSOGA that recorded $8.36 * 10^7$ bytes, $8.29 * 10^7$ bytes, $8.31 * 10^7$ bytes and $8.82 * 10^7$ bytes respectively. Moreover, the total data delivered by aHSSOGA is the highest compared to other existing methods where it recorded $3.22 * 10^1 1$ bytes of data. This shows that the proposed aHSSOGA performed better in this metric compared to HSAPSO, HFAPSO, HGWOSFO and HSSOGA by 28.57%, 24.84%, 21.12%, 12.42% respectively. Meanwhile, the average data delivered over the network is $6.74 * 10^7$ bytes for HSAPSO, $6.83 * 10^7$ bytes for HFAPSO, $6.92 * 10^7$ bytes for HGWOSFO, $7.54 * 10^7$ bytes for HSSOGA and $7.94 * 10^7$ bytes for proposed aHSSOGA. These results shows that the proposed aHSSOGA managed to deliver better amount of data over the network which ensures quality inter-cluster communications. To ensure the significance of the results, a statistical test using One-way ANOVA is carried out and its results are tabulated in Table 6.10 below.

Table 6.10: Statistical analysis of total data delivered metric using "One-way ANOVA (Tukey's test)" between aHSSOGA and the other existing methods using Re-Clustering after a Node Dead (R-CND)

Algorithm (I)	Algorithm (J)	Mean Difference (I-J)	p-Value (Sig.)
aHSSOGA	HSAPSO	**9.61E+07***	**< 0.001***
	HFAPSO	**8.91E+07***	**< 0.001***
	HGWOSFO	**8.15E+07***	**< 0.001***
	HSSOGA	**3.23E+07***	**< 0.001***
*. The mean difference is significant at the 0.05 level.			

From the statistical test results, aHSSOGA has showed significance performance compared to HSAPSO, HFAPSO, HGWOSFO and HSSOGA a significant level of 0.05. This also strongly shows that the proposed method is able to transfer more data to be analyzed because of its efficiency in data transfer and longer network lifetime.

The network throughput recorded for all the compared methods using R-CND clustering technique are depicted in Figure 6.10 below.

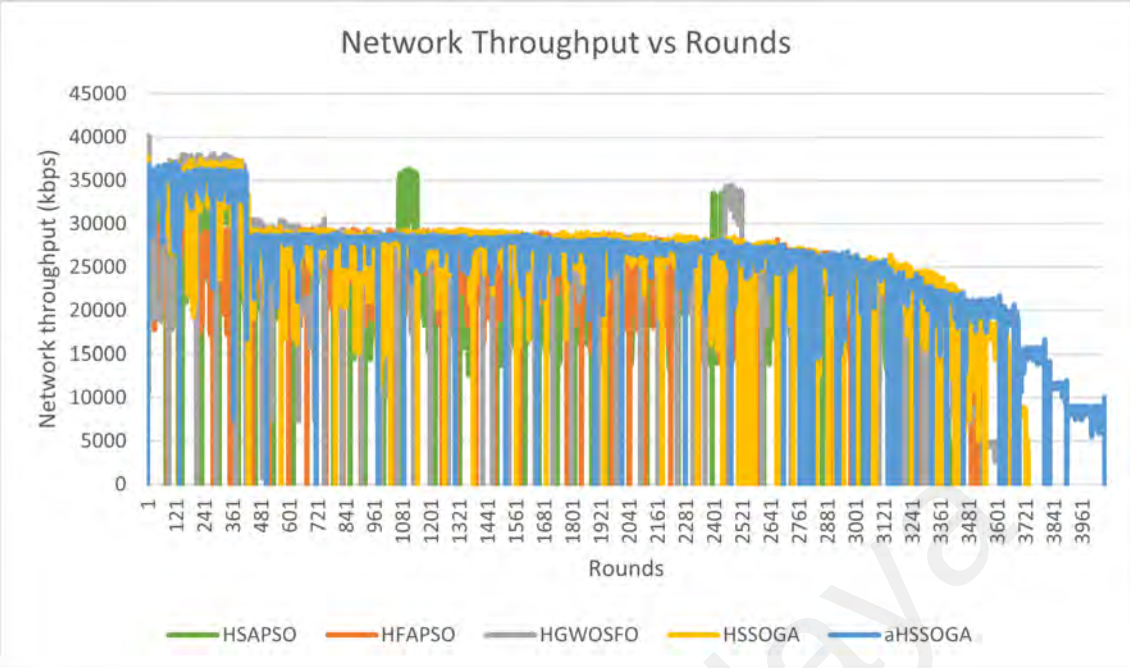

Figure 6.10: Network Throughput over Number of Rounds using Re-Clustering after a Node Dead (R-CND)

From the graph above, it can be analyzed that HSSOGA and HGWOSFO had a higher throughput in early stages compared to the proposed aHSSOGA. HSSOGA manage to obtain the highest average network throughput throughout the network cycle where it recorded an average of 25928.86 kbps, comparing to HSAPSO, HFAPSO, HGWOSFO and aHSSOGA that recorded 24146.14 kbps, 25257.43kbps, 25445.47kbps, and 25585.63 kbps respectively. This could be a cost of slightly higher complex computation aHSSOGA in adjusting its exploration and exploitation. The significance of these results is shown in Table 6.11 below.

Table 6.11: Statistical analysis of network throughput metric using "One-way ANOVA (Tukey's test)" between aHSSOGA and the other existing methods using Re-Clustering after a Node Dead (R-CND)

Algorithm (I)	Algorithm (J)	Mean Difference (I-J)	p-Value (Sig.)
aHSSOGA	HSAPSO	**1439.49***	**< 0.001***
	HFAPSO	328.20	0.152
	HGWOSFO	140.16	0.864
	HSSOGA	-343.24a	0.111
*. The mean difference is significant at the 0.05 level.			

The statistical results above shows that the aHSSOGA shows significant performance compared to HSAPSO method only. However, this metric can be evaluated based on last few rounds to ensure the accurate communication efficiency performance of the network.

Adaptive HSSOGA can also be said to have a stable network throughput towards the end of network operational network cycle as shown in Figure 6.11 below.

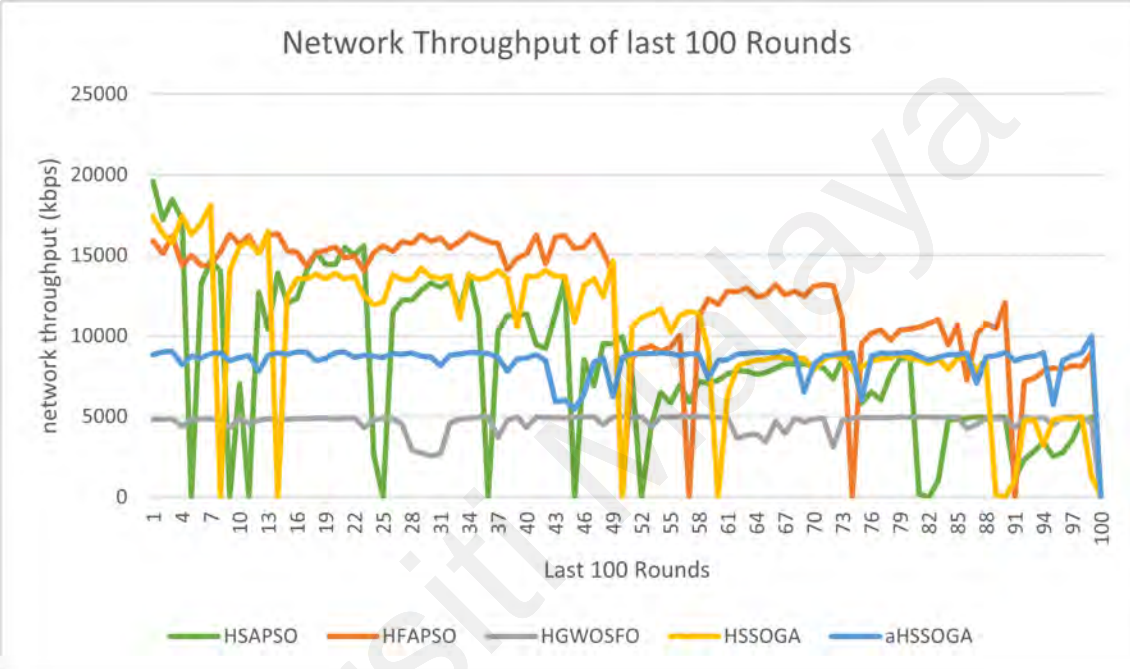

Figure 6.11: Network Throughput of LEACH and aHSSOGA in the last 100 rounds using Re-Clustering after a Node Dead (R-CND)

From the graph above, it can be seen that HSAPSO, HFAPSO and HSSOGA have network throughput near to zero a few times towards the end. This shows that the data transfer is inefficient when there are fewer alive nodes. This is said to encounter the same phenomenon discussed in section 6.3.1 of this chapter that the network faces issues such as isolated node problems and energy hole problems. Even though HSSOGA uses refined objective function with isolated node probability and node degree factors, it dips in network throughput that can be caused by inefficient CH selection in real-world application such as WSN. This is where the superiority of aHSSOGA is seen to have adaptive changes of exploration and exploitation capability in selecting the optimal CH for efficient network communications. In conclusion, aHSSOGA showed more stable network communication with lesser alive nodes which makes the network to be functioning efficiently towards the end. These results are tested with One-way ANOVA (Tukey's test) to ensure the stability of aHSSOGA towards the end of network lifetime.

Table 6.12: Statistical analysis of network throughput in the last 100 rounds of the network lifetime metric using "One-way ANOVA (Tukey's test)" between aHSSOGA and the other existing methods using Re-Clustering after a Node Dead (R-CND)

Algorithm (I)	Algorithm (J)	Mean Difference (I-J)	p-Value (Sig.)
aHSSOGA	HSAPSO	188.07	0.996
	HFAPSO	**-3950.82***	**< 0.001***
	HGWOSFO	**3822.91***	**< 0.001***
	HSSOGA	**-1832.12***	**0.002***
*. The mean difference is significant at the 0.05 level.			

Adaptive HSSOGA has outperformed HFAPSO, HGWOSFO and, most importantly outperformed its non-modified version of HSSOGA, which verifies the discussion above on the characteristic of aHSSOGA on real-world applications. To further analyse the communication efficiency in the R-CND clustering technique, a graph is drawn based on the method end-to-end delay across the network rounds depicted in Figure 6.12 below.

Adaptive HSSOGA has recorded a stable end-to-end delay as there are not many fluctuating delays observed from the graph above compared to HSAPSO, HFAPSO, HGWOSFO and HSSOGA. The lowest average end-to-end delay is recorded by aHSSOGA, which is 0.0166ms compared to HSAPSO that recorded 0.0173ms, HFAPSO that recorded 0.0202ms, HGWOSFO that recorded 0.0214ms and 0.0191ms. The average recorded in last 100 rounds are 0.048ms, 0.03ms, 0.034ms, 0.032ms and 0.026ms for HSAPSO, HFAPSO, HGWOSFO, HSSOGA and aHSSOGA. This proves again the efficiency of aHSSOGA towards end of network lifetime. The statistical test result below shows the significance performance of the proposed method compared to the other existing methods.

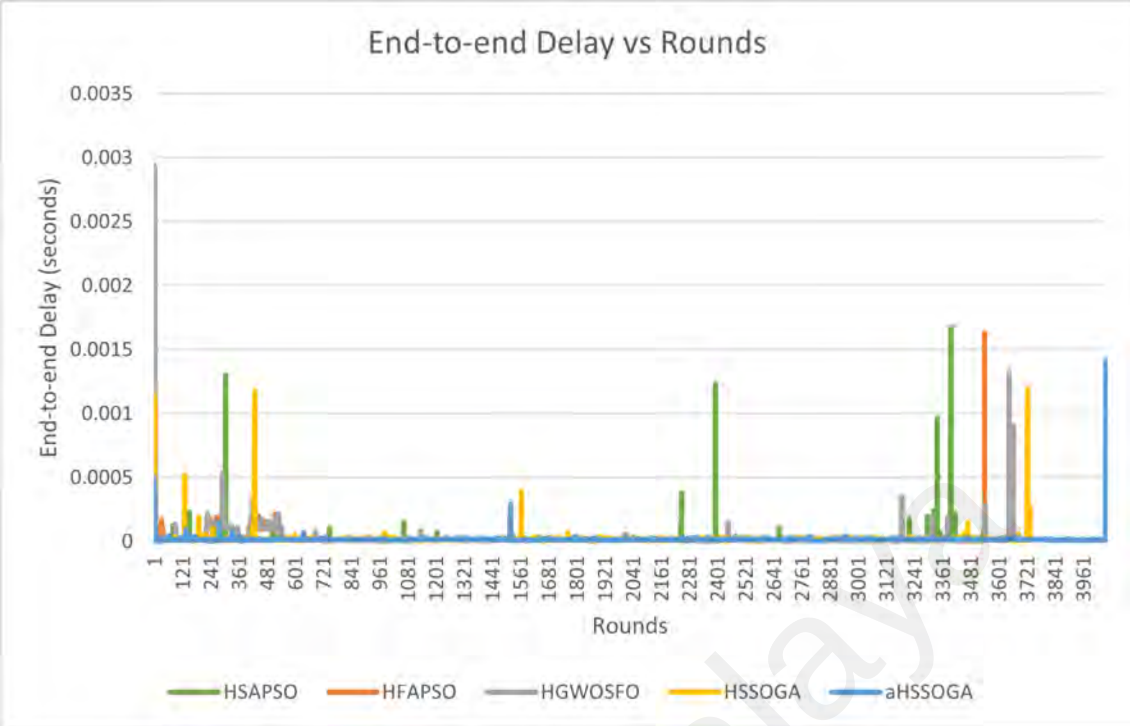

Figure 6.12: End-to-end Delay over Number of Rounds using Re-Clustering after a Node Dead (R-CND)

Table 6.13: Statistical analysis of end-to-end delay metric using "One-way ANOVA (Tukey's test)" between aHSSOGA and the other existing methods using Re-Clustering after a Node Dead (R-CND)

Algorithm (I)	Algorithm (J)	Mean Difference (I-J)	p-Value (Sig.)
aHSSOGA	HSAPSO	-7.33E-07	0.975
	HFAPSO	**-3.65E-06***	**0.021***
	HGWOSFO	**-4.80E-06***	**0.001***
	HSSOGA	-2.49E-06	0.223
*. The mean difference is significant at the 0.05 level.			

From the Table above, it shows that aHSSOGA has shown significant performance compared to HFAPSO and HGWOSFO at a significant p-value of 0.05. This shows that aHSSOGA performs better using R-CND clustering technique because it shows significant performance compared to 2 other methods, where in the previous evaluation using the enhanced LEACH clustering technique, it only showed significant performance compared to LEACH, that is a single hop-based method. In conclusion, aHSSOGA ensures stable inter-cluster communications from the start to the end of the network lifetime.

6.4 Discussion

This section describes a detailed discussion of the results obtained above and the pros and cons of the proposed method. Not only that but to ensure a thorough analysis is done, the time and space complexity of the proposed method, aHSSOGA, is also discussed in this section.

6.4.1 Enhanced LEACH Clustering Method vs Re-Clustering after a Node Dead (R-CND) method

The main idea of proposing a new clustering technique is to reduce frequent clustering that costs energy consumption overhead. The enhanced LEACH clustering behaves similarly to LEACH but will only be triggered if the average energy has dropped 10% compared to the average energy recorded during the previous clustering process. On the other hand, R-CND is proposed to reduce re-clustering frequency even more by only triggering the re-clustering process if an alive node is detected as dead. From the results, it can be analyzed that using the enhanced LEACH clustering technique ensures that the initially deployed nodes remain alive for a longer period compared to the R-CND technique. However, R-CND has a longer network lifetime than the enhanced LEACH clustering technique. This is because the enhanced LEACH technique ensures that the node with lesser energy is selected as CH even though the node is not dead, causing more re-clustering calls. In contrast, R-CND only calls the re-clustering process to select the CH with a higher energy level once a node dies. This comparison between these techniques is depicted in Figure 6.13 below.

From the graph above, aHSSOGA using enhanced LEACH clustering, managed to keep all 100 nodes alive up to round 1879, and aHSSOGA using R-CND, only managed to keep all nodes alive for 133 rounds. However, the last node dead recorded by aHSSOGA using R-CND is at round 4059, while aHSSOGA using enhanced LEACH clustering recorded

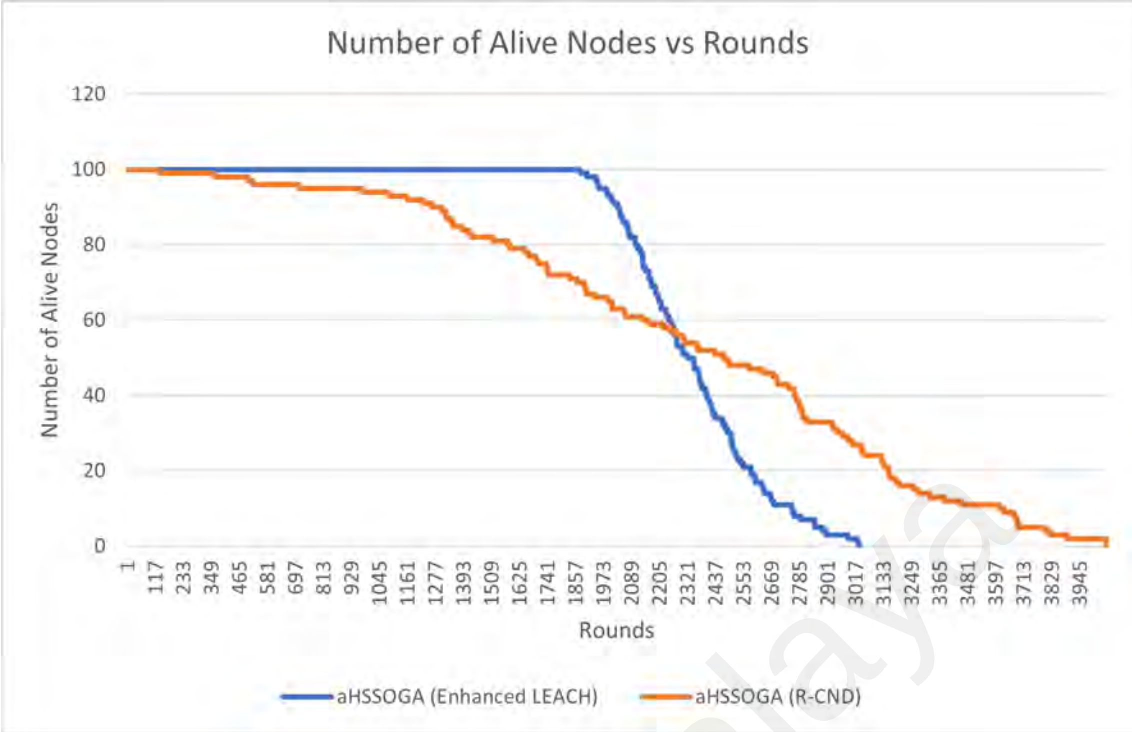

Figure 6.13: Network lifetime comparison of enhanced LEACH clustering and R-CND technique using aHSSOGA for CH selection

the last node dead at round 3034. This can be concluded that enhanced LEACH clustering enables a network to function with a higher number of nodes longer, providing better coverage for a longer period than the R-CND technique. This clustering technique can be used for applications focusing on intrusion and event detection (Chowdary & Bera, 2022). However, not all applications need complete coverage, such as water level monitoring in rivers, temperature monitoring in forests and environmental data monitoring (Tripathi et al., 2018). So, these applications only require partial coverage but a longer network lifetime, which makes R-CND a more suitable technique.

6.4.2 Space and time complexity of aHSSOGA

Space and time complexity is an important element in determining the efficiency of the built algorithm. Adaptive HSSOGA has a space and time complexity similar to HSSOGA because aHSSOGA has just a few more steps to adjust the crossover and mutation probability. The space complexity of an algorithm is the amount of space required in the memory for the execution of the algorithm. Initially, the population is created in an array of n size. Each element in the array is set to hold another array with the maximum number of CH allowed at a time, k as the length, which makes the space required as $O(n) * O(n) = O(n^2)$. Through the iterations, two other populations of equal size to the initial population are created with different lengths, named crossover and mutated populations. The crossover populations have the length of $pc * n$ where pc is the crossover probability that changes adaptively. The crossover population still holds an array of k length in it. Moreover, the mutated population is an array with the length of $pm * n$ where pm is the adaptively adjusted mutation probability. These arrays have the same space complexity of $O(n^2)$. These populations are also merged and truncated to the initial population to have a single population with the best solutions where the velocity of Sperms is used to update the position of the population, which has a space complexity of $O(n)$. So, the overall space complexity of the proposed aHSSOGA is as such, $O(n^2) + O(pc * n * k) + O(pm * n * k) + O(n) = O(n^2)$.

The compared algorithms termed HSAPSO, HFAPSO and HGWOSFO have the same space complexity as the initial population created has a population with the length n, and every element in the array holds another array with length k, as such, the space complexity of these algorithms is $O(n * k) = O(n^2)$.

Time complexity, on the other hand, speaks about the time taken to run the algorithm given the input length. As discussed in the space complexity section, aHSSOGA has a similar time complexity to HSSOGA even though it adaptively changes the crossover and mutation probabilities. The algorithm initially sets the total amount of iteration it has to go through, making the time complexity $O(n)$. The time taken to calculate the stated objective functions can be stated as $O(n)$, which makes the time complexity in iteration

$O(n * n) = O(n^2)$. Since the crossover and mutated population are merged and sorted for velocity and position update implementation, the time complexity for these processes is stated as $O(nlogn)$. This brings to the overall time complexity inherited by aHSSOGA and HSSOGA as $O(n) + (O(n^2) * O(nlogn)) = O(n^2logn)$.

Algorithms such as HSAPSO and HFAPSO have a time complexity of $O(n^2)$ because of the simplicity of the algorithm. The iteration loop that is initially set is to have a time complexity of $O(n)$, and within the loop, the objective function is calculated, as well as the loop for the velocity and position update have a time complexity of O(n) which makes the overall complexity to be $O(n * n) = O(n^2)$. Furthermore, HGWOSFO is a unique algorithm that depends on the index number to decide whether GWO is performed or SFO is performed. However, the time complexity of this algorithm remains the same regardless of whichever conventional algorithm is executed. The iteration that is set initially carries a $O(n)$ complexity, followed by the objective function calculation in the main iteration loop that adds another $O(n)$ complexity. So, the overall time complexity for HGWOSFO is the same as the other two algorithm's complexity which $isO(n * n) = O(n^2)$.

In conclusion, aHSSOGA and HSSOGA have a higher time complexity compared to the other compared algorithms. However, aHSSOGA and HSSOGA have shown amazing performances by ensuring better network stability and inter-cluster communication than the other existing algorithms. The reduction in time complexity of the proposed method can be another research on its own, and it can be kept as a future work to this research.

6.4.3 Advantage and Disadvantages of proposed aHSSOGA for CH selection

Adaptive HSSOGA performs well in most of the above evaluations, which shows its capability to find globally optimal solutions in real-world scenarios such as the WSN field. The advantages that are observed are outlined below:

- Adjusting the crossover probability percentage *pc* and mutation probability percentage *pm* enables the algorithm's exploration and exploitation in the search for the global solution. Besides, adaptively adjusting the sperm's motility rate ensures the algorithm is set to explore the search regions or exploit the searched regions. So, this produces the appropriate CH to be selected.
- Adaptive HSSOGA selects optimal CHs that reduces the isolated node problem and energy hole problem where it records a low end-to-end delay and slower energy exhaustion towards the end of the operational network cycle.
- The network lifetime is greatly enhanced by aHSSOGA in both the proposed enhanced LEACH clustering technique as well as the R-CND technique. Adaptive HSSOGA also managed to show stable network communications between nodes, CHs and BS with stable throughput.

There are always no perfect solutions in this world so there are several disadvantages possessed by aHSSOGA as outlined below:

- The time complexity of the algorithm is higher compared to other methods because of the use of crossover and mutation operators. Moreover, the refined objective function may take some extra time to calculate compared to the existing method's objective function.
- Adaptive HSSOGA may not perform well in high dimensional scenarios as adaptive adjusting probabilities may take up time, space, and extra energy overhead.

6.5 Chapter Summary

This chapter discusses the results obtained after implementing the proposed aHSSOGA in Chapter 5 of this thesis. The evaluation metrics are described and elaborated at the beginning of this chapter. The evaluation is based on the stability of the network that comprises metrics such as average residual energy (E_r), network lifetime (FND, HND, LND) and number of re-clustering occurrences. Besides, the evaluation of inter-cluster efficiency is also measured using the total data delivery (TDD_r), network throughput ($Throughput_r$) and end-to-end delay metrics (EED_r). The evaluated results are depicted in two categories which are evaluation using the enhanced LEACH clustering technique and R-CND technique. The results from the simulation of methods in the WSN environment from MATLAB R2021a are described in Figures 6.1 to 6.13 and Tables 6.2, 6.3, 6.8 and 6.9. To prove the significant performance of the proposed aHSSOGA in certain metrics, a One-way ANOVA (Tukey's test) is performed with a significant level of 0.05 and the results of this test are described in Tables 6.1, 6.4, 6.5, 6.6, 6.7, 6.10, 6.11, 6.12 and 6.13. From the results, we can deduce that aHSSOGA has outperformed HSAPSO, HFAPSO, HGWOSFO and conventional HSSOGA by having a stable clustered network and efficient inter-cluster communications. Some results are hard to be explained based on the graphs drawn as there are thousands of values involved. So, a detailed results collection has been made, for example, the values from the last 100 rounds of all the compared methods are obtained for analysis as shown in figure 5 and 11. Upon the results, a discussion is made for the comparison between the two clustering methods, enhanced LEACH clustering and Re-Clustering after a Node Dead (R-CND) technique. Following that, a discussion on the space and time complexity of the proposed aHSSOGA is done, showing that aHSSOGA has a similar space and time complexity as the non-adaptive version of the method. However, the time complexity of HSSOGA and aHSSOGA is not low as the other methods, as it is left as a future research opportunity to refine the proposed method. Lastly, a discussion on the advantages and disadvantages of aHSSOGA in CH selection is made, where several advantages in terms of exploration and exploitation are explained, and disadvantages based on time complexity compared to other existing methods are also outlined.

CHAPTER 7: CONCLUSION AND FUTURE WORKS

This chapter focuses on providing an overall concluding remark of the work that has been explained throughout this thesis. So, this chapter ensures the revisitation of the problem statement, objectives, and contributions. Besides, the limitations and future direction based on this work are described briefly as well. The chapter is organized as follows: First, an overview and conclusion of the thesis section 7.1. In section 7.2, a brief explanation of the achieved objectives and contribution of this thesis is given. Finally, the chapter is concluded with limitations and the future direction of this thesis in section 7.3.

7.1 Overview and Overall Conclusion

Wireless Sensor Networks (WSNs) is envisioned to be used in fields such as environmental monitoring, disaster prevention and military surveillance system to collect valuable data that enables us to avoid future disaster or intrusions. In WSNs, the nodes are usually deployed randomly by dropping the sensor nodes from air transport to a particular field that is being monitored. These small nodes have sensing units such as Zigbee, Wi-Fi and LoRa for communication with limited memory and energy. Since these nodes are deployed in difficult to reach area, it is important to ensure the energy of the nodes are preserved for a longer network lifetime. LEACH ensures the nodes are clustered and a CH is selected for data transfer, reducing energy consumption during transmission.

Clustering is where a few nodes are selected to be the head, and other nodes join the head for data transmission, which forms multiple clusters of nodes. However, this method caused isolated node problems and network hole problems because of inefficient Cluster the Head (CH) selection that quickly deteriorates the network lifetime. As such, clustering using metaheuristic methods is implemented to select optimal CH given extending network lifetime, as it is more cost-efficient and easier to implement. Nevertheless, a theory of having balanced exploration and exploitation capabilities in a metaheuristic method can help the method to select CH optimally. Therefore, we proposed a hybrid metaheuristic method with a good balance of exploration and exploitation capabilities. Even though there are many existing hybrid metaheuristic methods from the literature, the idea of having a balanced exploration and exploitation is not explored in depth, and the problem of isolated node issue and energy hole issue still exists with a non-proper refinement of the objective functions. As such, in this work, we have proposed a hybrid metaheuristic method named Hybrid Sperm Swarm Optimization and Genetic Algorithm (HSSOGA) in Chapter 4 and Chapter 5 enhances the proposed method to be applied in WSN to have adaptiveness in exploration and exploitation capabilities which caters the changing values of the node's energy and status. The proposed solutions for the challenges faced are described in the objectives of this thesis. In the next section, the achieved objectives and contributions are described.

7.2 Achieved Objectives and Achieved Contributions

In this thesis, an adaptive hybrid metaheuristic method for optimal clustering in a WSN environment is presented. To achieve this goal, four main objectives were outlined in Chapter 1, section 1.4 of this thesis. In this section, we will revisit the stated objectives and discuss the process of achieving these objectives.

The first objective is to ensure a survey of all the existing optimization and clustering methods of WSN by exploring the literature from journals articles of ISI Web of Science databases. Moreover, the second objective of this thesis is to develop a hybrid metaheuristic method that balances both exploration and exploitation capabilities in view of enhancing a metaheuristic method's performance. The third objective is to select optimal CH by avoiding isolated node and energy hole problems by implementing the proposed metaheuristic method with adaptive exploration and exploitation capabilities with refined objective functions. Finally, the last objective is to evaluate and validate the proposed method using simulations and comparing results with several existing metaheuristic methods in the literature. A comprehensive explanation of how these objectives are accomplished is described below.

- Exploring the literature on metaheuristic methods by understanding their advantages and limitations: This objective is achieved by reviewing the existing methods in the field of WSN. It is known that LEACH is the base of clustering methods which was proposed in the early 2000s (W. R. Heinzelman et al., 2000). A detailed review has been made of over 300 literature from journal articles and conferences on WSN from databases such as IEEE Xplore, IEEE Access, Hindawi, Science Direct and many more (ISI Web of Science databases). Metaheuristic methods are categorized into hybrid and non-hybrid versions, where hybrid versions are set to enhance the non-hybrid version to ensure the metaheuristic method can solve an optimization problem. The objectives of the literature, selection criteria (objective function) used, and advantages and limitations of the literature are outlined for a better understanding of the use of the method and to obtain the research gap for this research. Besides, modified and extended versions of metaheuristic methods are also reviewed to obtain a good knowledge of the capability of the methods. The summary of the literature and its details are described in Chapter 2 of this thesis.

- Developing a hybrid metaheuristic method that balances both exploration and exploitation capabilities: From the literature, it is ensured that the balance between exploration and exploitation capabilities unlocks the better performance of metaheuristic methods (Xu & Zhang, 2014). The obtained literature has highlighted the advantage of Sperm Swarm Optimization (SSO), which is deemed to be an exploitation-based algorithm, and Genetic Algorithm (GA), which is an exploration-based algorithm. The objective is achieved by hybridizing these two algorithms to have balanced exploration and exploitation capabilities as well as they work as a trade-off for their algorithm's limitation. The development of Hybrid Sperm Swarm Optimization and Genetic Algorithm (HSSOGA) is explained step-by-step procedure in Chapter 4 of this thesis. The pseudocode of HSSOGA is provides in section 4.2.3. To ensure its performance the method is used to optimize a set of unimodal and multimodal test function to obtain global solutions. The test functions used are Sphere, Sum Square, Zakharov, Rosenbrock, Step, Griewank, Ackley, Schwefel 2.26, Michalewicz and EggCrate functions (Jamil & Yang, 2013; Surjanovic & Bingham, 2013). The evaluations are made according to four metrics which are the quality of results in the form of mean, μ and standard deviation, σ (statistical comparison), along with the convergence rate of the method to global solutions. The best fitness and average best fitness obtained over 30 independent runs are also obtained to ensure the quality of results (numerical comparison). The results are compared to its conventional methods, which are SSO and GA. Besides, some existing hybrid methods are also used for results comparison, such as HFPSO, HPSOGA, SAGA, PSOGWO, and HSSOGSA. To ensure the significance of the obtained results One-Way ANOVA Tukey test is applied to all the comparisons. The results and discussions indicate that the proposed HSSOGA opens the ability of the method to be used in real-life scenarios such as WSN with the ability to adjust the exploration and exploitation rates. The proposed HSSOGA outperformed HFPSO, SAGA, PSOGWO and HSSOGSA in all 11 test functions.

- Implementing the proposed hybrid metaheuristic method with adaptive exploration and exploitation capabilities in clustering of WSN: It is learned that isolated node problems and energy hole problems are two vital problems in WSN from the literature review. To mitigate this issue, the developed HSSOGA is enhanced with adaptive exploration and exploitation capabilities to select optimal CHs according to the network's status, which is this thesis's objective. The adaptiveness of the method depends on the crossover population and mutated population's fitness, where the crossover probability and mutation probability are adjusted as described in Chapter 5, section 5.3.2. Besides, the velocity of the population is also decreased linearly to ensure better convergence of the method towards a global solution (selecting appropriate CH). The pseudocode is presented in Chapter 5 of this thesis. This adaptive HSSOGA (aHSSOGA) is then implemented into cluster head selection and cluster formation of WSN, which ensures this objective is achieved. A refined objective function that consists of the average distance between candidate CHs and other candidates CHs, the average distance between the candidate CHs and member nodes in a cluster, average residual energy of the candidate CHs, candidate CH's maximum neighbour node degree, and average isolated node probability, as well as improved clustering techniques namely enhanced LEACH clustering as well as Re-clustering after a Node Dead (R-CND), are proposed to ensure the quality of network is maintained. The network environment is focused on static random node deployment in a 100 x 100m area with 100 nodes, as it is the standard network environment stated by many literatures. Moreover, a multi-hop data transmission environment is implemented to ensure better network lifetime and communication efficiency. These implementations are simulated using MATLAB R2021a simulation tool.

- Evaluating and validating the proposed adaptive hybrid metaheuristic method with a set of performance metrics: The proposed adaptive method was evaluated based on six performance metrics which are average residual energy, network lifetime, number of re-clustering occurrences, total data delivery, network throughput and end-to-end delay. The evaluated results are validated by comparing five existing methods, namely LEACH, HFAPSO, HSAPSO, HGWOSFO and the non-adaptive HSSOGA. The results are compared on two categories with each of the proposed clustering techniques. In the R-CND technique, the LEACH method is omitted from the comparison because the nature of its clustering technique that does not suit the proposed R-CND. To ensure the significance of the results obtained, a One-Way ANOVA Tukey test is conducted on the obtained results from average residual energy, total data delivery, network throughput and end-to-end delay performance metrics. The proposed aHSSOGA was able to show a good performance in all aspects compared to LEACH, HFAPSO, HSAPSO, HGWOSFO and HSSOGA. Thus, making the proposed adaptiveness a valuable contribution to obtaining optimal CHs and forming good clusters in WSN. The space and time complexity of the method is also discussed, which gives a good idea of the future direction of this research. Besides, a comprehensive discussion is provided to verify the quality of the proposed adaptive HSSOGA and the refined objective function that is implemented to mitigate the isolated node and energy hole problem of WSN. Following that, a complete discussion of proposed clustering methods is also discussed, and it can be extended into future research as well.

The achieved contributions of this work to the body of knowledge are briefly explained in the points below:

- Hybrid Sperm Swarm Optimization and Genetic Algorithm (HSSOGA): HSSOGA consists of SSO, which is well known for exploitation, and GA, which is well known for its exploration features. These methods are hybridized to ensure the usage of a single population to crossover, mutate and have a velocity to update the positions. The method proposed to solve global optimization problems is to obtain global solutions. The comparison of HSSOGA and other existing hybrid methods are depicted in tables of Chapter 4.

- Adaptive Hybrid Sperm Swarm Optimization and Genetic Algorithm (aHSSOGA) for cluster head selection and cluster formation: The adaptiveness of the proposed method is to cater for the ever-changing parameters of WSN environments such as energy level and node status. The modified version of HSSOGA changes the crossover probability and mutation probability based on the previous fitness obtained by the crossover and mutated populations. The velocity dampening factor is also linearly decreased to ensure that the population explores in the beginning and exploits towards the end of iterations. This process ensures that the method adaptively suits itself to the environment changes.

- Refined objective functions: The objective function to select CHs is refined compared to other literature that includes the average distance between candidate CHs and other candidate CHs, the average distance between the candidate CHs and member nodes in a cluster, average residual energy of the candidate CHs, candidate CH's maximum neighbour node degree and average isolated node probability. These objectives ensure the isolated node and energy hole problems are reduced by appropriate CH selection by the proposed adaptive hybrid method.

- Enhanced clustering techniques: Enhanced LEACH technique is proposed to have a similar feature to LEACH clustering where re-clustering only happens every 10%

drop in average energy compared to the previous round to ensure reducing the re-clustering frequency which reduces the overhead energy usage. On the other hand, the Re-clustering after a Node Dead (R-CND) method is used even to reduce the re-clustering frequency more than enhanced LEACH clustering, where re-clustering only occurs after a node is completely dead. The enhanced LEACH method is proposed for applications that need high coverage, such as intrusion detection and even detection systems. At the same time, R-CND applies to applications, such as environmental monitoring systems, that require partial coverage, as discussed in Chapter 5.

7.3 Limitation and Future Direction

Every research is to provide a better solution for an issue, but the existence of limitations on certain aspects can still be identified. The obvious limitation obtained from this thesis is the time complexity of the proposed method. Even though the proposed method has obtained greater results, the algorithm still has higher time complexity because of the nature of using GA's crossover and mutation operators. This will fit as a future direction of this research to optimize the algorithm further to obtain better time complexity than the existing methods.

Secondly, WSN is considered a big topic with various scopes. The characteristics of WSN comprise network deployment, clustering, channels, signal transmission and reception, medium access control, congestion control, routing algorithms and many more. However, this thesis only focuses on cluster head selection and cluster formation processes. So, in the future, this thesis can be extended to study the other characteristics of WSN networks using the proposed methods.

Thirdly, in the WSN implementation of the adaptive hybrid metaheuristic method, it is only considered for static random node deployment in a 100 x 100m area. This might not suit every other application, such as animal tracking systems, coverage in obstacle area systems and vehicular network systems. As such, future work can be extended to implement the proposed method in animal tracking and vehicle-to-vehicle (V2V) communications network. As well as implementing the proposed method in different field sizes could be a future direction as well. Moreover, analysing the proposed hybrid method in larger-scale networks would enable a deeper analysis of the robustness and scalability of the metaheuristic method.

In addition, the multi-hop communication that is discussed in this thesis is based on the shortest path first method to transfer data towards BS. But in some large networks with bigger area makes, the process is more complex for multi-hop communication. The proposed adaptive HSSOGA can also be extended to use to create optimal routing paths for networks such as mobile ad hoc networks (J. Wang et al., 2009) and Optical Burst-Switched (OBS) networks (Pedro et al., 2009).

Furthermore, the proposed method can be used for data mining and text mining as big data mining is a demanding topic with a high research value currently. This is because metaheuristic methods are deemed to have more straightforward implementation and better optimization. Not only that, the existence of deep learning and machine learning can extend the research work to explore these processes to carry out clustering in WSN.

Lastly, adjusting the parameters of the proposed method yielded a better result, as such, the compared algorithms, such as HFAPSO, HSAPSO and HGWOSFO, can be adaptively adjusted as well to suit the optimization scenario for better results which can be considered as future work.

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