Optimized Multi-Superframe Scheduling for Clustered Wireless Sensor Networks

by

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The above committee determined that the thesis is acceptable in form and content and that a satisfactory knowledge of the field covered by the thesis was demonstrated by the candidate during an oral examination. A signed copy of the Certificate of Approval is available from the School of Graduate and Postdoctoral Studies.

ABSTRACT

Since the power source for wireless sensor networks (WSN) is mainly from batteries, prolonging network life is an important requirement of the network. Hence, clustering algorithms are employed to decrease the number of packets in the network via data aggregation as well to reduce packet network collisions by adopting scheduled communication among nodes in a cluster. The composition of the superframe plays an important role in scheduling the communication among the nodes in the network as well as determining the application data rate of acquisition. The differential evolution (DE) algorithm is used to fulfill the objective, to maximize network life under different data acquisition rate. The data acquisition rate is dependent on the IEEE 802.15.4e superframe. In addition, the multi-superframe structure is utilized to enable nodes to conserve more energy. The proposed method provides a set of solutions, based on the constraints and goals.

Keywords: Wireless Sensor Network (WSN); LEACH clustering; IEEE 802.15.4e; Multi-superframe; Differential Evolution (DE)

AUTHOR'S DECLARATION

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STATEMENT OF CONTRIBUTIONS

The following contributions are presented in this thesis:

- The multi-superframe structure is used for application-driven scheduling with respect to appropriate data acquisition rates and maximizing network life concurrently.

- For the first time, it evaluates a combination of differential evolution (DE) optimization and multi-superframe structure in order to satisfy the following objective.

- maximizing the average energy of the network under different data acquisition rates.

It shows that DE based low energy adaptive clustering hierarchy (LEACH) outperforms the existing LEACH in different applications.

- Since other network simulation, can not be configured easily and return the remaining energy to the evolutionary algorithm. A new simulation environment based on Python and "Simpy" is created. Integration between an evolutionary algorithm and simulation is a compelling reason for creating a customized simulation.

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sole authorship

I hereby certify that I am the sole author of this thesis and that no part of this thesis has been published or submitted for publication. I have used standard referencing practices to acknowledge ideas, research techniques, or other materials that belong to others. Furthermore, I hereby certify that I am the sole source of the creative works and/or inventive knowledge described in this thesis.

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LIST OF ABBREVIATIONS AND SYMBOLS

BI	BI Beacon Interval
BO	BO Beacon Order
BS	Base Station
CAP	CAP Contention Access Period
CFP	Contention Free Period
CSMA/CA	Carrier Sense Multiple Access with Collision
CH	Cluster Head
CDMA	Code-division Multiple Access
DE	Differential Evolution
EA	EA Evolutionary Algorithm
GA	Genetic Algorithm
GTS	Guaranteed Time Slots
LEACH	Low Energy Adaptive Clustering Hierarchy
LMAC	Lightweight Medium Access Protocol
RSSI	Received Signal Strength Indicator
PSO	Particle Swarm Optimization
SDN	Software-Defined Network

SO	Superframe Order
TDMA	Time-division Multiple Access
WSN	Wireless Sensor Network

Chapter 1. Introduction and motivation

1.1 Introduction

Networks of wireless sensors offer numerous applications and opportunities to significantly impact our lives. One of the most important domains of IoT devices is in industries such as factories and agriculture. Greenhouses behave as factories and benefit from IoT, from dynamic management to control the temperature, vents, and productivity. Sensors mainly detect light, humidity, and temperature as a means of monitoring while also simultaneously utilizing emergency applications. In all applications, the restriction is battery life [1] causing a reduction in network life. To address this issue, the adequate type of clustering algorithms is employed to decrease the number of packets in the network. Due to the fact that the alert operation drives our timing and clustering schedule, none of the traditional clustering algorithms consider the applications and superframe structure in order to reduce energy consumption. Moreover, many attempts are made to solve the network lifetime problem nowadays. To remedy non-application-based management, this thesis focuses on a higher level of network management and superframe to demonstrate a trade-off between two objectives. To find an optimal superframe size and composition two objectives are used; the network-dependent objective, which is energy, and the application dependent objective, which is the data acquisition rate.

The superframe is a part of the medium access control (MAC) layer frame which consists of slots that synchronize the communication between the sensor nodes in a wireless sensor network (WSN).

The superframe structure is made to control synchronization and deterministic delay which consists of two parts, an active and an inactive period. In the inactive period, nodes go into standby mode in order to preserve power. The active period consists of two parts: The contention access period (CAP) and the contention-free period (CFP). In the inactive part, nodes go to sleep mode leading to the conservation of energy.

The superframe size is traditionally dependent on superframe order (SO) and beacon order (BO), however, this thesis considers guaranteed time slots (GTS), contention access period (CAP) slots and inactive slots instead. This approach is more accurate in terms of energy conservation since GTS slots are collision-free slots and are bound with cluster formation. Moreover, the multi-superframe structure which is a combination of two superframes enables our method to conserve more energy. The last important factor is that the application ‘s data acquisition rates are considered as the optimization’s constraint as well.

In this thesis, an evolutionary algorithm is used. It should be taken into consideration that defining a multi-objective optimization problem is very difficult. Due to the fact that different domains like greenhouses and emergency settings have different data acquisition rates and goals, namely monitoring and alert systems. Hence, the motivation is whether an optimal superframe can facilitate appropriate data acquisition rates and energy consumption simultaneously. The objectives need to be prioritized based on application and network demands.

After applying an evolutionary algorithm, a set of solutions called the Pareto front is made. The optimal superframe size and composition will then be selected considering the applications with equal or lower data acquisition rates. In the end, the optimal superframe size and composition will be applied for the WSN.

1.2 Problem Statement

WSNs are in charge of supporting different applications, hence, to address the trade-off between diverse data acquisition rates and energy consumption, it is necessary to compute an optimal superframe size and schedule. This is a multi-objective problem.

1.3 Thesis Statements

Based on the problem statement above, this thesis aims to investigate whether an evolutionary algorithm can effectively be trained to find a set of optimal superframe schedules for clustered WSN operating under diverse acquisition data rates.

To that end, a combination of evolutionary algorithms with clustering formation and leveraging IEEE 802.15.4e is investigated.

1.4 Contributions

The following contributions are presented in this thesis:

- The multi-superframe structure is used for application-driven scheduling with respect to appropriate data acquisition rates and maximizing network life concurrently.
- For the first time, it evaluates a combination of differential evolution (DE) optimization and multi-superframe structure in order to satisfy the following objective.
    - maximizing the remaining energy of the network under different data acquisition rates.
- It shows that an optimized superframe outperforms the existing superframe in different applications.
- A new simulation environment based on Python and "Simpy" is created. Integration between an evolutionary algorithm and simulation is a compelling reason for creating a customized simulation. Also, the real-time configuration of the simulation by an evolutionary algorithm is not an easy task.

1.5 Paper submitted

A paper titled "Optimized Application Driven Scheduling for Clustered WSN" has been submitted to the IEEE International Symposium on Networks, Computers, and Communications (ISNCC2020) conference.

1.6 Thesis Organization

This thesis presents the introduction, motivation, and problems. The remaining chapters of the thesis are organized as follows. Chapter 2 provides a literature review of clustering and optimization in WSN. Chapter 3 discusses the proposed optimization method. Also, it includes an overview of the MAC layer and the IEEE 802.15.4e standard. Moreover, the superframe structure and the multi-superframe structure will be introduced. Chapter 4 provides the different aspects of the simulation and an overview of the optimization phase and the results. Chapter 5 presents the sensitivity of our proposed method and how it can be affected by the duration of time and network configuration. Chapter 6 shows the way to apply the result in a network. Chapter 7 contains the conclusion of this research and proposes some potential future directions.

Chapter 2. Literature review

Several papers that are relevant to different parts of the current thesis are discussed in this section. The literature review focuses on four dimensions: (a) industrial wireless sensor nodes, (b) clustering formation on wireless sensor network (WSN), (c) the MAC layer protocols relevant to this research; and finally, (d) optimization used in cluster formation and superframe size.

2.1 Industrial Wireless Sensor Network

Each sensor node consists of components, for instance, hardware components, microcontrollers, communication devices, operating systems, and an energy system. There are numerous wireless sensor nodes that are based on different configurations and features regarding their application. The structure of a node is mainly related to the trade-offs between price, features, and application [2]. In the agriculture industry, sensor nodes and actuators are used to measure soil temperature, soil moisture, air temperature, air humidity and light intensity/alert messages, water level, pressure precision agriculture, water, electrical conductivity, temperature irrigation, solenoid valves precision irrigation wind speed, wind direction, humidity, rain gauge, water, and pH level crop fields, and solar radiation vineyard. All of them mainly suffer from short battery life [1]. Hence, energy-saving is vital in WSN. Both microcontrollers and communication devices should go to sleep mode as long as possible they should sleep and they can wake up based on a timer or an event [2]. Shibata et al. [3] explained the execution time and energy consumption in CC2650 SensorTag, such as transition and receiving energy consumption. In comparison with sensing, communication is demanding in terms of energy [3].

2.2 MAC Protocol

In this thesis, time-division multiple access (TDMA) and carrier sense multiple access (CSMA), are used, hence the medium access control (MAC) is explained in this part. Since MAC is top of the physical layer (PHY), PHY has a great influence on MAC. The main function of MAC protocols is time coordinating for nodes to access the shared medium. There are various causes of energy wastage like overhearing, collisions, overhead, and idle listening. Hence, these features should be taken into consideration in order to design MAC protocols. Although putting in sleep mode can alleviate the problem of energy consumption, it can increase the delay and throughput as well [2]. Although the inactive part leads to extend the node’s life, it affects the data acquisition rate. Hence, both objectives should be optimized at the same time.

The protocols can be generally classified into the following classes: fixed assignment protocols, demand assignment protocols, and random-access protocols.

● Fixed assignment protocols: the TDMA scheme subdivides the time axis into fixed-length superframes and each superframe is divided into a fixed number of time slots. The

TDMA requires precise time synchronization between nodes to avoid overlapping and collisions.

● Demand assignment protocols: the particular allocation of resources to nodes is made on a short-term basis, typically the duration of a data burst. This class can be subdivided into centralized and distributed protocols.

● Random access protocols: when a node desires to transmit a new packet, it transmits the packet immediately. There is no coordination with other nodes so the risk of collisions is high. In the CSMA protocols, a transmitting node attempts to be respectful to ongoing communications. First, the node is expected to listen to the medium then if the medium is detected to be idle, the transmission begins. Otherwise, the node postpones the transmission for the future by manipulating several possible algorithms. Also, the RTS/CTS handshake, busy-tone solution, and a back-off algorithm can reduce the number of collisions.

The transmitting is costly, hence, transmission and reception energy consumption costs are almost the same. The decisive factor of designing the MAC layer is to conserve energy. Some of the properties in energy problems and design goals are collisions, protocol overhead, overhearing, and idle listening [2]. In this thesis, the TDMA and CSMA concept is utilized.

2.3 Hierarchical Architecture

In order to save energy, hierarchical architectures are recruited and categorized into two groups: cluster-based and grid-based approaches [4]. In comparison with the grid-based approach, cluster-based is more common.

In the cluster-based approach, one of the main motives behind using LEACH_C as a centralized clustering algorithm is to facilitate central network management. Also, routing traffic successfully in WSNs, guarantees reliable network performance, but it faces many challenges due to the nature of the network: a) limited battery life of sensor nodes b) different applications of the network c) different quality of service (QoS) such as data acquisition rate, d) the ability to reconfigure the networks.

2.3.1 Cluster Network

The main feature of the cluster network is dividing the network into clusters. Each cluster has a selected cluster head (CH), which is defined by the CH selection process. Then the cluster formation phase plays its own role. The re-clustering is needed in order to find another cluster head under different circumstances [4].

Many algorithms are employed for cluster formation and cluster head selection. Each node in a wireless sensor network can play three different roles, such as a simple node (SN), gateway node (GN), and cluster head (CH). Gateways are engaged in aggregating and sending data to other clusters [5]. There are two types of communication within a cluster: intra-cluster in a single-hop cluster and inter-cluster when it is multi-hop between clusters [4].

WSNs tend to aggregate data of the sensor nodes in the clusters, in order to reduce the network traffic leading to more energy saving. The sensor nodes send the data to their dedicated CH then the aggregated data will be sent to the BS [6]. Node clustering in WSNs has many advantages, such as scalability, energy efficiency, and reducing routing delay [7]. The main objective of clustering is energy conservation [6].

There are three clustering characteristics, namely: cluster properties, the CH properties, and the clustering process properties.

Specification of clusters play a vital role in cluster properties such as 1) the number of clusters, which can be constant or variable, 2) cluster size, which can be equal or unequal, 3) intra-cluster communication, which can vary based on the algorithms, 4) inter-cluster communication, 5) the distance between the node and the BS.

In the CH properties, CH selection has a significant effect on the performance of algorithms. CH properties include 1) mobility of CH, 2) type of node in heterogeneous or homogeneous networks, 3) the role of the CH, which can be a simple relay node or can play an important role such as data aggregation/fusion based on the algorithm.

In terms of the clustering process properties, some features should be taken into consideration, for instance, 1) the method used centralized or distributed, 2) the clustering objectives mentioned before, 3) the CH election algorithms which are derived by random, present and attribute-based methods, the complexity of the algorithm and also the nature of the algorithm, can be reactive or proactive, 4) the last feature is network dynamism, which can be dynamic or static [6].

There are several surveys in clustering architecture in WSN which show the importance of these structures to save energy and to reduce the amount of controlling packets in the network for instance [5] [8] [9] [10].

2.4 Software-Defined Networks and Clustering

Also, some papers attempted to use software-defined networks (SDN), since SDN has a central manner of management [8] and the current thesis is going to use the central management concept some SDN paper, will be reviewed.

Biradjar et al. [9] divided routing algorithms into three groups such as 1) flat routing, which leads to transfer of all data to base station (BS) causing high energy consumption, 2) location-based, which is based on the geographical position of nodes, 3) hierarchical, which assigns each cluster to a CH to aggregate the data forwarded to the base station. The main problem of this paper was the lack of protocols for WSN such as 802.15.4 and the absence of SDN.

Flauzac et al. [5] tried to use multi BSs as hosts for SDN controllers in each cluster and provided software-defined clustered sensor networks (SDCSN). Also, SDN controllers can exchange information together. The OpenFlow protocol is used to establish the SDN controller connection. The authors tried to figure out the optimal place for the SDN controller in WSN using a clustering mechanism. In their idea nodes should recognize the flow table entries. In addition, they provided the cluster solution to remedy the energy problem and place SDN controllers in the cluster head.

They also provided a hierarchical approach to cope with multiple controllers in SDN with the cluster-based solution that aggregates data in the CH and sends it to the BS. Sensor nodes have access to the policies and routing decisions via the CH that plays a BS role on its cluster and every neighbor domain communicates with its neighbors. LXC containers that were nested to *openvswitch* were recruited to test their approach and a collaborative manner was used between the CH to manage the traffic flows [5].

Aslam et al. [10] provided the SDN-based Application-aware Centralized adaptive Flow Iterative Reconfiguring (*SACFIR*). Hence, they used SDN and clustering simultaneously to maintain the load-balancing flow and calculate the cost of the flows. In their algorithm, SDN controllers reside in each BS. Their goal was to make adaptive reconfiguration management on WSN with centralized management. Since clustering protocols' emphasis is energy efficient, they employed clustering which is a good remedy for SDN unacceptable latency and energy consumption.

They compared Application-aware Threshold-based Centralized Energy-Efficient Clustering (ATCEEC) and Multi-hop Centralized Energy-Efficient Clustering (MCEEC) protocols with two routing protocols at Inter-Networking Processing (INP) level namely *SACFIR* and its extended version, *SAMCFI*. *ATCEEC* and *MCEEC* suffer from a lack of real-time management and use static iterations for re-clustering, which is not energy efficient enough. SDN-controller makes the routing decisions based on data gathered in the network discovery phase, then the flow table is sent to *SACFIR-Visor* that is located in the application layer. Moreover, *SACFIR-Visor* should ensure that the SDN controller implements the received response.

Based on initial energy resources, the sensor nodes are divided into three categories: normal nodes, advanced nodes, and supernodes. In each round of *SACFIR* and *SAMCFI*, they have three phases: Network Topology Management Phase (NTMP), the Network Settling Phase (NSP) and the Network Forwarding Phase (NFP). In the *NTMP* phase, the topology discovery (TD) is sent periodically to get updated information and have an updated global view of the network. In the NSP phase, they do re-clustering every 10th period. Since SDN is aware of the global view of the network, it calculates overall residual energy and selects Forwarding Elements Cluster-Heads (FECHs) based on higher energy, centrality, and the minimum distance between FECHs and the BS. After that, every *FECH* starts to advertise and the other nodes based on their Received Signal Strength Indicator (RSSI) choose the appropriate one which has less energy communication cost.

Due to the fact that inter-communication and intra-communication are energy-consuming, this method can save energy. Thus, SDN calculation tries to minimize the cost of these two kinds of communication by recruiting a greedy algorithm. In the NFP phase, the main differences between SACFIR and SAMCFI are application-specific transmission constitutes the path selection difference in the transmission phase. In SACFIR, unique multipath inter-cluster communications are employed for all reports while in SAMCFI, the same method is used and in addition, critical information, the node is triggered to communicate directly.

Finally, they implemented the methods and compared the network lifetime, stability, end-to-end delay and packet delivery ratio with *ATCEEC* and *MCEEC* protocols [10].

Sankar et al. [11] proposed a multi-layer cluster-based energy-aware routing protocol for Low Power and Lossy Networks (LLN). They divided the network to equal length rings with equal size of clusters. The routing protocol for low power and lossy networks (RPL) is standardized by IETF, RPL employs Destination-Oriented Directed Acyclic Graph (DODAG). In order to address the network lifetime problem, they proposed a Multi-layer Cluster-based Energy-Aware Routing Protocol (MCEA-RPL) for LLN which consists of three phases: ring creation, CH selection, and cluster formation and Expected Transmission

Count (ETX) and Residual Energy (RER) were used for optimal parent selection in inter-cluster routing based on fuzzy logic. In their protocol, the cluster member (CM) sends data to the CH node using the TDMA schedule while the CH node forwards the data to the parent node recruiting the CDMA schedule. Finally, they showed their protocol extended the network lifetime and increased the packet delivery ratio [11].

Lamda et al. [12] maintained that there are several similar works on RPL and clustering such as Improved RPL (IRPL), Opportunistic RPL (ORPL), the extension of ORPL (ORPLx), Cluster-parent based RP (CRPL), Efficient topology construction for RPL over IEEE 802.15.4, Energy-Efficient Region-Based RPL (ER-RPL), Hybrid, Energy-Efficient, and cluster-parent based RPL (HECRPL), Energy-efficient heterogeneous ring clustering routing protocol (E2HRC).

There are numerous challenges that can be taken into consideration namely: centralized vs decentralized CH selection, randomly vs deterministically based on energy CH selection, distance and the number of nodes, overhead and load balancing, time and delay. On the other hand, there are numerous changes in cluster formation as well, such as intra-cluster communication, inter-cluster communication, and overhead on cluster formation [7].

2.5 Centrally Managed Cluster Networks Algorithms

This section will mention some centralized cluster algorithms like LEACH-C [4] and APTEEN [6]. There are numerous ways of categorizing clustering algorithms, for example, equal size vs unequal size [6], centralized vs decentralized. This thesis mainly looks into centralized clustering. Equal size algorithms try to maintain equal size clusters and small ones with minimum overlaps such as Low Energy Adaptive Clustering Hierarchy (LEACH). It aims to prolong the network lifetime and use a random selection of CH. Hence, it tries to rotate and share the role of the CH between the nodes [13].

One of the first and significant hierarchical algorithms, which is energy-efficient is called LEACH. Since LEACH has CH random selection, the role of the CH rotates periodically which brings about the reduction of energy in the network. In the simple form of LEACH cluster formation and CH-selection are done locally. This local selection not only decreases the traffic from nodes to the sink but also ensures the scalability of the network. There are two operation phases in LEACH: setup phase and steady phase. In the setup phase, the CH is elected and advertises itself and in the steady-state phase, supports data aggregation and transmission [7]. There are different versions of LEACH such as a multi-hop version of LEACH, also known as M-LEACH [14], and centralized LEACH, which uses a centralized architecture. The LEACH-C has a scalability problem since having a large number of nodes impose heavy controlling packets traffic. LEACH can save energy as much as 8 times in comparison with the other routing techniques [9].

TEEN [15] is another equal size algorithm and uses hierarchical architecture to decrease the number of transmissions, which leads to saving energy. Having said that, there are several demerits like lack of feedback and problem in defining the thresholds. Also, cluster head changes periodically inside the cluster [9].

Unlike LEACH, in TEEN algorithm data is sent to the BS only when the event occurs and the main idea is based on data-centric protocols in the hierarchical structure. There are soft and hard thresholds in TEEN which are used for transmission of data to the BS. Thus, the node sends the data to the CH only when it senses the hard threshold. The soft threshold only is used for no change or little change of state, which leads to transmit without data to the CH. In this architecture, the data of the CH is gathered by the next level CH until received by the BS. Since TEEN reduces the traffic on the network, the approach is energy efficient. As a result of the data-centric nature of TEEN, it is more suitable for time-concerned applications which are used for quick response demand or urgent situations.

TEEN has several problems namely, firstly, there is no feedback until the threshold is reached. Consequently, some nodes die without any warning. Secondly, defining the threshold is quite challenging. Finally, since it suffers from a lack of periodic updating, it is not appropriate for monitoring applications. Hence, adaptive threshold sensitive energy efficient sensor network (APTEEN) as an improvement of TEEN was made. TEEN is a hybrid method to support both reactive like TEEN and proactive like LEACH. After the CH election, it starts to broadcast schedules, count time, thresholds and attributed to the members. Therefore, based on these features each node sends the data when it senses the hard threshold. Also, data is collected periodically from regular nodes and aggregated data on CHs. There are other problems in APTEEN. One of them is the complexity of thresholds and another one is the CH election, which is centralized on the BS and as a result causes less scalability [6].

Several efforts have been made to prolong the network life such as clustering algorithms that utilize the cluster formation to decrease the number of packets and save energy in the networks. Generally, clustering algorithms are oblivious to the application-dependent features. Also, they are not aware that superframe size and its composition can impact cluster formation and energy consumption which can be problematic. Historical algorithms only rely on network-dependent features such as distance to the base station, energy, centrality, and other network criteria.

2.6 Optimization in WSN

Many studies apply optimization on WSN such as cluster formation optimization, finding the optimal size of the superframe and scheduling in order to minimize energy consumption. First, optimization on cluster formation will be reviewed and then the papers relating to the evolution algorithm on superframe size will be discussed.

2.6.1 Optimization of cluster formation

Many papers exist that apply optimization for evaluating the optimal clustering formation namely Han et al. [16]. In order to achieve the goal of energy conservation, they investigated parameters such as residual energy, distance from nodes to neighbors, the base station, and the number of neighbors through weighting. They optimized parameters for neighbor communication range R and weight coefficient W of clustering factors. Their work demonstrated that the network lifetime lasts over 1.4 times of previous approaches. Also, it showed a significantly reduced energy consumption. Finally, they concluded that there is a trade-off between the quality of service and time delay on WSN.

Mittal et al. [17] defined several objectives and used spider monkey optimization (SMO) to prolong the network lifetime. Their proposed method showed better energy consumption, system lifetime and stability period in comparison with existing protocols. They had some clustering objectives, for instance, energy consumption, cluster quality (maximization of the cluster distribution), CH residual energy, and scheduling time to create the optimal cluster formation.

Similarly, Mahesh et al. [18] proposed a hybrid optimization algorithm named dolphin echolocation-based crow search algorithm to address the cluster head selection. The performance is evaluated using three metrics, namely network energy, lifetime, and throughput. They evaluated the multiple objectives problem, such as energy, delay, mobility, inter-cluster distance, intra-cluster distance, and link lifetime in WSN. In the end, the proposed algorithm offered a better network lifetime with higher energy remaining. There have been numerous papers that have investigated optimization on cluster formation and CH selection.

A few works were not oblivious to network applications, and the effect of the application is taken into consideration by Hu et al. [19] proposed energy-efficient adaptive overlapping clustering (*EEAOC*). They divided WSN applications into categories such as event-based, continuous monitoring, query-driven, and hybrid applications. They proposed a hybrid strategy that toggles between time-driven and event-driven schema to support the QoS requirement with a longer network lifetime. Since re-clustering imposes a heavy overhead on the network, a "query message" strategy is used to detect an event requiring re-clustering. The results demonstrated that for the dynamic continuous monitoring applications the *EEAOC* achieves a longer network lifetime cycle.

2.6.2 Optimization of superframe size

Some works considered superframe size optimization as an important factor in WSN. Beacon order (BO) and superframe order (SO) are the main factors of their work. For example, a priority-based superframe structure is proposed by Henna et al. [9] to reduce the contention in the CAP period. They achieved low energy consumption, high throughput, and low latency by applying a method called traffic adaptive priority-based MAC (TAP-MAC). They evaluated better results in emergency traffic, on-demand traffic, and normal traffic compared to the standard IEEE 802.15.4 based on different performance metrics such as network throughput, average end-to-end delay, and average energy consumption.

Hassan et al. [20] provided a combination of dynamic priorities for traffic differentiation and dynamic duty cycle adaptation in the GTS allocation. Unfixed BO and SO can improve the performance of the IEEE 802.15.4 protocol namely, end to end delay and power consumption in both real-time monitoring and real-time emergency communication. They demonstrated that dynamic duty cycle was successful in scenarios with high priority, for example, an emergency event application demands to have low latency meanwhile WSNs expected to have minimization on power consumption.

Optimization on WSN can be applied based on different scenarios and applications. Also, optimization has been investigated on many network features, for example, many surveys evaluated superframe size, BO and SO. Kim et al. [21] evaluated the performances for instance throughput, packet delay distribution, packet loss probability, and energy consumption by optimizing the lengths of the beacon interval and the active period. Their goal was to prolong the lifetime of devices regarding satisfying quality-of-service which includes packet delay and packet loss probability. Finally, they simulated and showed there was a trade-off between energy consumption and delay, but in the cases of (4,3) (3,2) Beacon Order (BO) to Superframe Order (SO) ratio was the optimal parameters for both objectives which are packet delay and packet loss. However, in terms of a longer lifetime (4,3), BO to SO ratio was optimal.

Khalifeh et al. [22] demonstrated to achieve the optimal performance on the network, the parameters should be optimized, for instance, a minimum end-to-end delay, minimum packet drop rate and maximum throughput. Hence the beacon and the superframe orders were evaluated on three scenarios with different cluster sizes and transmission rates. The results demonstrated that optimal values are three for both beacon and superframe orders.

Price et al. [23] provided that equal Beacon and Superframe orders are the optimal parameters. For instance, in terms of energy consumption and packet delivery ratio, BO = 6 and SO = 1 however to minimize the delay, BO = 1 and SO = 1 are the optimal ones.

Lee et al. [24] proposed a priority-based algorithm for adaptive superframe adjustment and GTS allocation (PASAGA) to modify the superframe in order to improve the goodput and delay for high priority data by dividing the GTS length. Hence the optimal value of BO and SO found and experiences showed outperformance of their proposed method regarding goodput, delay, and energy consumption in high priority situations in compression with the IEEE 802.15.4 standard.

Similarly, Salayma et al. [25] evaluated the optimal combination of (BO and SO) in terms of energy consumption, average end to end delay and throughput. Since diverse applications work through different arrival rates at different duty cycles, they define the objectives such as enhancing energy consumption, delay, and throughput. The results showed that the optimal parameters are aligned between [(6,6) and (8,8)] to decrease up to 7% in energy consumption and 16% in terms of throughput.

Satrya et al. [26] have evaluated the optimization with modified GA (MGA) and GA, EDF, DMS, PSO, and OLPSO and have proposed an optimized solution for Industrial WSN in order to decrease the defect time in superframe scheduling. Finally, they showed that modified GA (MGA) and GA outperformed competitors such as EDF, DMS, PSO, and OLPSO.

Kurunathan et al. [27] have proposed a dynamic multi-superframe tuning method which can adapt the multi-superframe structure based on the size of the network dynamically. Deterministic Synchronous Multi-channel Extension (DSME) benefits from the multi-superframe structure, but a fixed setting leads to throughput and increases the network delay. By manipulating their technique, throughput increased by 15-30% and also a 15-35% decrease in delay in comparison with DSME that has a static setting in six scenarios.

In this part, many papers have investigated BO and SO and superframe size by exhaustive search or classical methods since they maybe are prone to an integrated environment of evolutionary algorithm and simulation. In this thesis, DE is utilized to find the optimal superframe size and composition with respect to different data acquisition rates and application demands. The CSMA slots, the TDMA slots, and inactive slots are taken into consideration instead of SO and BO. It makes the problem more complex and more accurate in comparison to the previous works. Also, the main reason that the inactive part is important is to put nodes in the inactive mode which leads to energy conservation. The SO value only declares the active part including CAP and GTS together. The GTS is collision-free and has an impact on simulation results in terms of energy and packet resending. The previous works did not consider application demands and data acquisition rates either. Table 1 demonstrates a summary of these papers.

Table 1 Summary of optimization papers

Papers	Approaches	Variables /Method	Metrics
Mittal et al.	cluster formation optimization	Spider monkey optimization (SMO)	Energy consumption, Cluster quality (maximization the cluster separation) CH residual energy, Scheduling time
Mahesh et al.	cluster formation optimization	Effective communication and energy consumption	Energy, Delay, Mobility, Inter-cluster distance, Intra-cluster distance, link lifetime
Han et al.	cluster formation optimization	communication range R, weight coefficient W of clustering	Quality, Delay
Henna et al.	superframe size optimization	TAP-MAC	Network throughput, Average end-to-end delay, Average energy consumption

Hassan et al.	Superframe size optimization	Optimization GTS	Energy consumption, Real-time
Kim et al.	Superframe size optimization	BO and SO	Delay, Throughput, Energy consumption, Packet loss
Khalifeh et al.	Superframe size optimization	Superframe	End-to-end delay, Packet drop rate, Throughput
Prcic et al.	superframe size optimization	BO and SO	Packet delivery ratio, Received packets per consumed energy, Minimize the average delay
Lee et al.	superframe size optimization	GTS length	Throughput and delay for high priority data
Salayma et al.	superframe size optimization	BO and SO	Energy consumption, Delay, Throughput
Satrya et al.	superframe size optimization	Modified GA (MGA) and GA outperform EDF, DMS, PSO, and OLPSO	Minimize the defect time

Kurunathan et al.	superframe size optimization	Deterministic Synchronous Multi-channel Extension (DSME) MO, SO, BI and CAP Reduction	Throughput, Delay
Current work	superframe size optimization	CAP slots, GTS slots, Inactive slots, Multi-superframe structure	Data acquisition rate

Chapter 3. An Evolutionary Algorithm for Clustered WSNs

Prior to presenting a differential evolution (DE) algorithm for clustered WSN, it is necessary to know the background of the clustering algorithm and 802.15.4e protocol. Firstly, the IEEE 802.15.4e is reviewed in order to create the superframe and multi-superframe structure. The DE utilizes superframe/multi-superframe structures as genes of the chromosome, while cluster formation uses guaranteed time slots (GTS) slots for inter-cluster communication. Hence, the optimization algorithm is under the effect of cluster formation and the number of nodes in the cluster can impact the optimization results.

Prolonging the life cycle of WSN is the main objective in considering the energy consumption of the network. In addition, some applications demand high-frequency data so the system should address the quality attribute as well. For example, the main domain for applications can be industries such as greenhouses. The way that the proposed model works is that it starts by generating different sizes and compositions of superframe. Then the generated superframe is fed to simulation to calculate the remaining energy. The evolutionary algorithm tries to produce offspring that obtain more remaining energy. In the next step, based on the optimal set of solutions, the optimal solution will be selected based on the data rate of the applications and will be applied for the whole network. In Chapter 6 these steps will be explained in more detail.

3.1 The IEEE 802.15.4e Superframe

A protocol sets a trade-off between attributes such as throughput, latency, energy efficiency and radio coverage targeting application scenarios. For example, The IEEE 802.15.4-2011 is designed to work either on a beacon-enabled or a non-beacon enabled mode and utilize the superframe, that consists of an active period and the inactive period. During the inactive part, the node goes to sleep mode to preserve energy [28]. The active period is subdivided into 16-time slots which are partitioned in a contention access period (CAP) followed by a number (maximum of seven) contiguous guaranteed time slots (GTS). In non-beaconed mode, there is no synchronization technique, hence there are time synchronization issues.

IEEE 802.15.4e provides five different MAC behaviors, for instance, radio frequency identification (RFID), asynchronous multi-channel adaptation (AMCA), deterministic synchronous multi-channel extension (DSME), low latency and deterministic networks (LLDN) and the time-slotted channel hopping (TSCH). In TSCH, this MAC behavior provides reliability and a time-critical guarantee in some cases. The frequency hopping mechanism is used in order to improve reliability. The undesired collisions are reduced by using time-slotted communication links. Also, the TDMA is employed to facilitate collision-free transmissions [28].

There are main features that lead to saving energy in IEEE 802.15.4e namely, low energy (LE) which is intended for applications that can trade latency for energy efficiency. It allows a device to operate with a low duty cycle. Fast association also leads to energy efficiency. CAP reduction can reduce the size of the CAP leading to energy saving. In addition, the group acknowledges (GACK) reduces the latency and energy consumption by combining several acknowledgments into a single group acknowledgment packet. As a result of using light and more energy-efficient scheduling and routing algorithms, energy efficiency could be achieved [28]. Based on the IEEE 802.15.4e, a superframe is used to manage the scheduling and enable nodes to go to sleep mode.

3.2.1 Superframe structure

The superframe structure is made to control synchronization and deterministic delay which consists of two parts, an active and an inactive period. In the inactive period, nodes go into standby mode in order to preserve power. The active period consists of two parts: The contention access period (CAP) and the contention-free period (CFP). In the CFP part slots are dedicated to each node and can communicate in guaranteed time slots (GTS) with the TDMA mechanism while in CAP, nodes transmit in CSMA/CA mechanism. Generally, the active part of superframe size is divided into 16 time-slots, thus the duration of the superframe is associated with duration of time-slots that can be between 15.36 ms to 4 minutes based on IEEE 802.15.4. Sometimes the time unit is called a symbol, and it depends on the radio frequency (RF) band. For example, in 2.4 GHz RF, band each slot duration (*aBaseslotDuration*) equals about 60 symbols. Hence, 16 slots equal to 960 *aBaseSuperframeDuration* symbols which are 15.36 ms [25]. For crucial use, the CFP can take a maximum number of seven GTSs. Since it broadcasts time-slots at the beginning of each superframe, it is beacon-enabled [23].

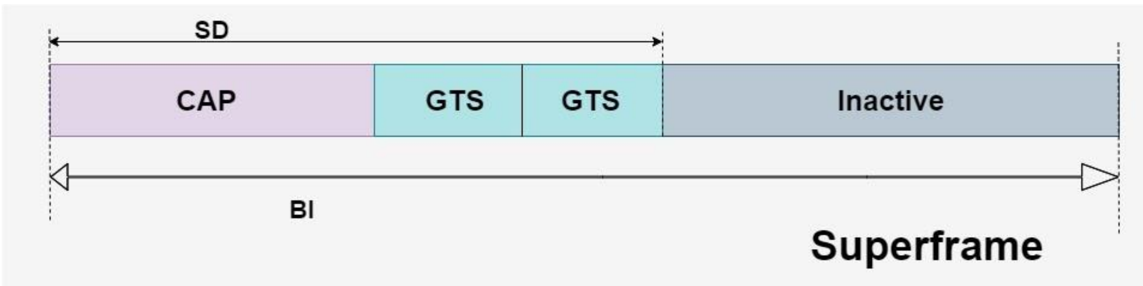

Figure 1 Superframe (SD, BI)

Because other researchers have used the BO and SO to calculate the superframe below are a set of equations that convert between BO and SO to Beacon Interval (BI) and Superframe duration (SD).

The *aBaseSuperframeDuration* value is defined by the minimum duration of a superframe.

Beacon interval (BI) is defined:

$$BI = aBaseSuperframeDuration \times 2^{\wedge}\mathrm{BO}$$

$$Where\ the\ BO\ is\ 0 \leq BO \leq 14 \qquad (1)$$

Superframe duration (SD) is defined:

$$SD = aBaseSuperframeDuration \times 2^{\wedge}SO$$

$$Where\ the\ SO\ is\ 0 \leq SO \leq BO \quad (2)$$

In order to obtain synchronization, in this thesis, a superframe is utilized to make a customized protocol with a duty cycle based on CAP and GTS slots instead of BO and SO as shown in Figure 2. The duty cycle mechanism is employed on top of the MAC protocol for active/sleep scheduling to conserve energy [29].

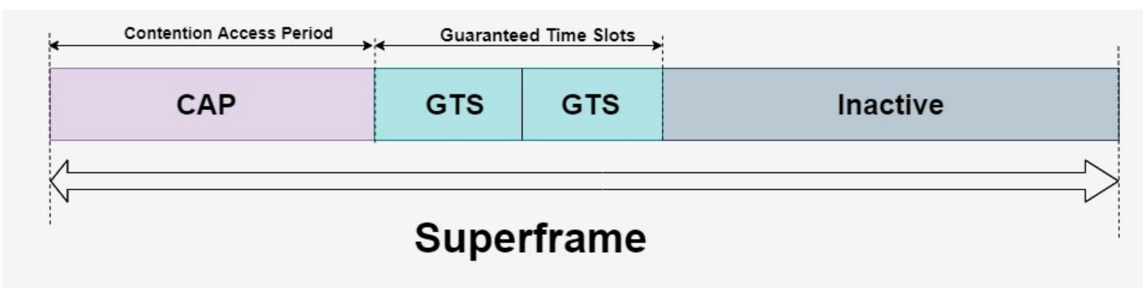

Figure 2 Superframe (CAP, GTS)

3.2.2 Multi-super framework structure

The multi-superframe structure is built by merging more than one single superframes together (in current case 2 superframes are used). The benefit of this structure is that nodes can send data in every other superframe leading to longer data acquisition rates and less energy consumption. Since 802.15.4e is restricted to a maximum to 4-minute intervals between the transmissions, for example utilizing the multi-superframe structure can extend the data acquisition rate to 8 minutes, which is helpful in monitoring applications that do not require fast acquisition rates.

For this execution phase, a customized multi-superframe structure is made to synchronize the simulation's communications as shown in Figure 3. Hence, each node can communicate in dedicated time slots.

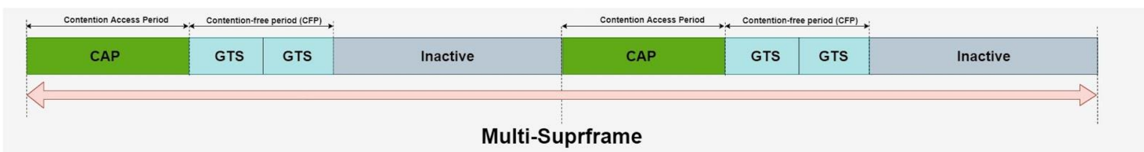

Figure 3 Multi-superframe

3.2.3 The relation between Superframe and WSN Cluster Communications

In the cluster, CAP slots are used for inter-cluster communication and GTS slots are utilized for intra-cluster communication. Since network configurations vary and cluster formation is related to GTS slots, the optimal values for CAP and GTS can vary as well. Moreover, in Figure 4 demonstrates the superframe size is related to the data acquisition rate, hence, it should be considered as per the application's demand. Finally, the evolutionary algorithm can benefit from these features to find the optimal solution. In the next chapter, the constraints for CAP and GTS will be explained.

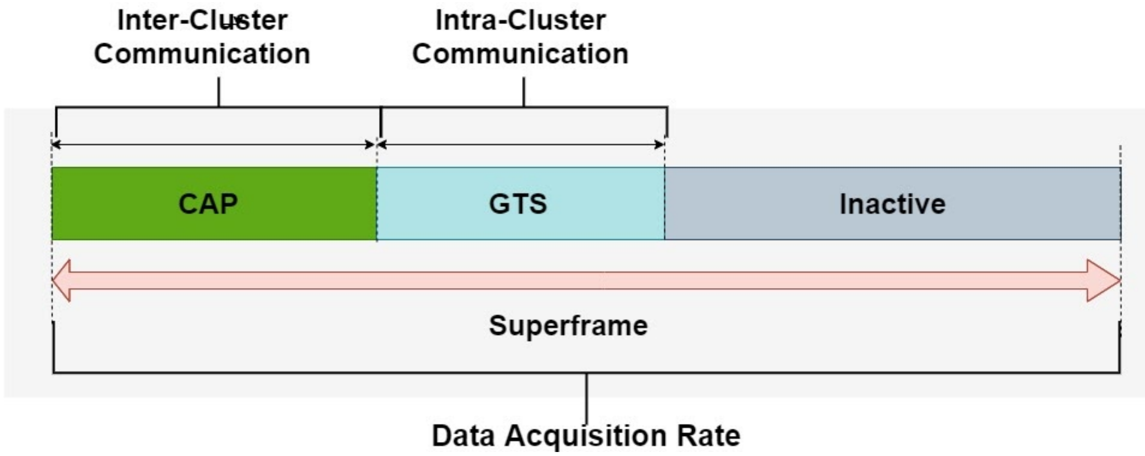

Figure 4 Superframe's composition and thesis

3.2 Optimization

The evolutionary algorithm is used in this thesis since the exhaustive search will fail to find any meaningful results in a vast search space. For converting a problem into an optimization problem, the first step is defining the variables. As previously mentioned, the DE algorithm begins with the creation of an initial population with some constraints. Then, all of them are evaluated using a specific fitness function which in this case is a simulation of the network that is used to calculate the remaining network energy after a specific execution time. DE is an efficient algorithm in the exploitation of the search space when there is a problem with a low dimension. In this thesis, optimization is utilized to address the design problem and, since genes are numbers, it is a discrete type of optimization. Moreover, due to the fact that the execution part can take time between days to weeks, it is considered as expensive optimization.

3.2.1 Differential Evolution

Differential evolution (DE) is a metaheuristic and stochastic optimization algorithm inspired by a genetic algorithm (GA). DE outperforms many other methods in terms of speed and robustness [30] which was introduced by Price and Storn in 1995 [31].

Like the other population-based evolutionary algorithm (EA), it starts with the creation of an initial population. By utilizing the number of population (Np), crossover rate (Cr), mutation scaling factors (F), and mutation schemes, the DE algorithm generates a new population-based on parent selection. The new generations are evaluated with the fitness function and could be replaced by a parent [32].

The creation of a candidate solution is based on a random combination of individual parents. Equation 3 represents the mutation operation, where Xr is a solution vector in the current population, and V is a mutant vector. F represents the scaling factor; hence, increased values bring about higher diversity:

$$V_{j,G+1} = X_{r1,G} + F\left(X_{r2,G} - X_{r3,G}\right) \tag{3}$$

Then in equation 4, DE generates a diversity of the population regarding crossover operation. $X_{i,G+1}$, which is a solution vector in population for the next generation, competes with the V vector based on *CR*. The *CR* is a crossover probability to create the trial vector (*U*).

$$U_{j,i,G+1} = \begin{cases} V_{j,i,G+1} \; if \; rand \; j,i \; \leq CR \; or \; j = I_{Rand} \\ X_{j,i,G+1} \quad\quad otherwise \end{cases} \tag{4}$$

The parent of the previous generation could be replaced by a candidate solution based on their fitness functions. In the end, the *U* vector can be replaced by a parent if it achieves a better fitness value [33].

$$X_{G+1} = \begin{cases} U_{i,G+1} \; if \; f(U_{i,G}) \leq f(X_{i,G}) \\ X_{i,G} \quad\quad otherwise \end{cases} \tag{5}$$

The DE pseudocode is described using pseudo-code as follows.

```
Generate initial population of individual (NP)
Do while
        For each individual j in population
                Select 3 random numbers, r1, r2, r3 with r1 ≠ r2 ≠ r3 ≠ j
                Generate a random integer I_Rand
                For each parameter I
```

$$U_{j,i,G+1} = \begin{cases} V_{j,i,G+1} & if\ rand\ j,i\ \leq CR\ or\ j = I_{Rand} \\ X_{j,i,G+1} & otherwise \end{cases}$$

```
                Replace X_{j,i,G+1} with child U_{j,i,G+1} if U_{j,i,G+1} is better
        End For
Until the termination condition isacheieved
```

3.2.2 Chromosome Generation

Each DE chromosome consists of four parts:

- GTS = The number of GTS slots
- CAP = The number of CAP slots
- Inactive = The number of Inactive slots
- MO = Multi-superframe {0} or Single-superframe {1}

The CAP is the number of slots for the CAP part of the superframe and the phenotype of that can be an integer number, based on the 802.15.4e standard. The GTS is the number of GTS slots which is part of the superframe, based on the 802.15.4e standard. The Inactive gene in the chromosome represents inactive slots of the superframe. The MO gene specifies whether the simulation uses a single-superframe or a multi-superframe structure.

Constraints come from the IEEE 802.15.4e standard. Moreover, the data acquisition rate can act as a constraint in the selection of the optimal solution in the Pareto front.

- $4 \leq GTS \leq 7$
- $1 \leq CAP \leq 9$
- $5 \leq CAP + GTS \leq 16$
- $0 \leq Inactive \leq 240 - (CAP + GTS)$
- Multi-superframe [0-1]

For GTS slots, the maximum value is 7 based on IEEE 802.15.4e, hence this number is set as the upper boundary for GTS slots. In a similar way, the number of CAP is limited to 9 regarding IEEE 802.15.4e and at least 1 slot is needed for inter-cluster communication. Due to the fact that the total active part can be divided into 16 slots, hence the sum of CAP and GTS slots cannot exceed 16. The last constraint is that the inactive part and active part should be a maximum of 4 minutes or 240 seconds. Moreover, if there is a strict application that demands specific and exact time, for example, t = X, the constraint can change to Inactive = X - (CAP + GTS) so the optimization will be simpler.

3.2.3 Fitness function

The main performance metrics evaluated by the simulation are data acquisition rate and the remaining energy of the network. Based on two main performance metrics, the fitness function is defined: the average residual energy-related a data acquisition rate which is bound to superframe size. In this case, the evolutionary algorithm benefits from the network simulator to calculate fitness function.

3.2.4 Termination condition

Generally, a 5000*Dimension fitness call is considered as a termination condition for the evolutionary algorithm. For example, with dimensions of 4 and a population size of 100, the algorithm's iteration is 200 times.

$$5000 * 4 = 20{,}000\ calls$$

$$20{,}000/100 = 200\ iteration \tag{6}$$

In this execution phase, each call is time-consuming in the network simulation since it is an expensive problem, hence, 3,100 calls are set in 31 iterations with 100 populations. In these experiments, the population generation took between 12 hours to 4 days (based on simulation duration time) executing on an environment that is set up as follows CPU: Intel Core i5-8250U 1.6 GHz; RAM: 8 GB; System: Windows 10.

Finally, the optimization algorithm maps 4-dimension variables space (CAP size, GTS size, Inactive size, MO) to objective space (the remaining energy consumption related to the superframe size) as shown in Figure 5.

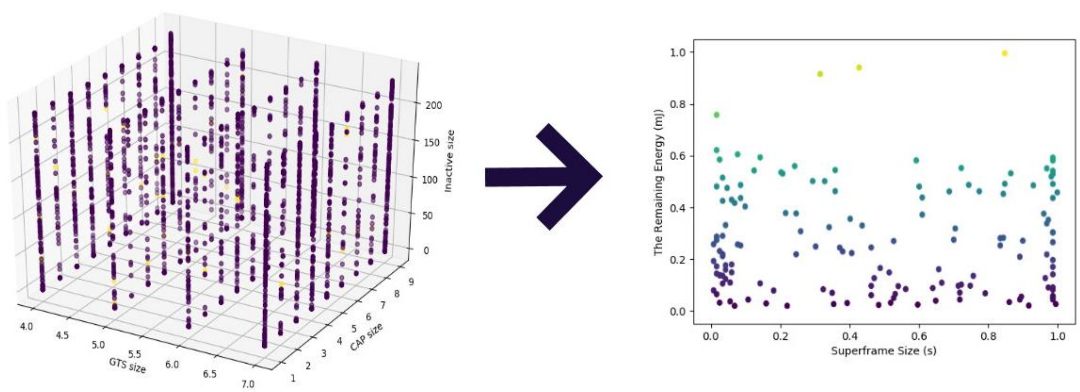

Figure 5 The mapping of dimensions to objectives

Chapter 4. DE Algorithm Methodology

In the DE algorithm phase methodology, DE generates the population-based on mutation and crossover. Each superframe configuration (chromosome) is fed to the simulation, and after a specific duration of time, the remaining network energy will be calculated by simulation and will be returned to the DE algorithm as the fitness function as shown in Figure 6. Hence, a new population will be generated to gain more remaining energy.

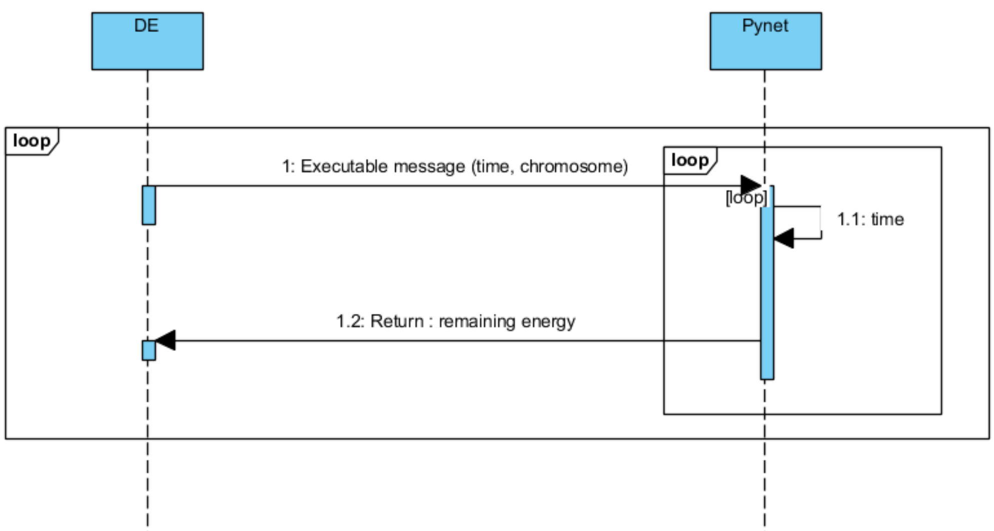

Figure 6 The sequence diagram of DE and Pynet

These steps repeat for all population and finally, DE will come up with a set of solutions.

In the next parts, firstly, the low energy adaptive clustering hierarchy (LEACH) steps are explained in the simulation. Due to the fact that decentralized clusters are unaware of the applications' demand, a centrally coordinated LEACH (LEACH-C) clustering algorithm is utilized for cluster formation.

4.1 LEACH-C Cluster Algorithm

Energy conservation is the main objective of any WSN therefore, TDMA communication scheduling and periodically changing the cluster head are utilized to preserve the energy in intra-cluster communication. The LEACH is a common clustering algorithm as per the literature. The main reason that central-LEACH is selected as a clustering algorithm over distributed LEACH is that the clusters demand synchronized communication while distributed LEACH brings more interference and collisions. Also, in current work, the network is single-hop since the bigger size of the network leads to heavier traffic. The initial steps include a discovery phase as defined below:

- The base station (BS) sends a node initialization message
- The neighbor tables of each node are created
- All nodes broadcast (an ID, IP or MAC address), residual energy, neighbor table, and distance from the BS. (the distance is a vital feature for selecting the CH)
- The BS uses the metrics of the nodes to define the CH for each cluster based on several rules such as residual energy and distance.

In this CH selection step, cluster heads will be selected based on the nodes data mentioned above and the following rules:

- Rule 1: Two CHs cannot be within communication range of each other
- Rule 2: CH's energy should be bigger than the specific threshold
- Rule 3: The CH should have at least N neighbor nodes

CH selection is an independent task from other nodes and is based on the probability of becoming the CH, the current round, the number of chosen CH in the past *1/p* rounds. The node will be announced as a CH due to the fact that its number is less than *T(n)*. Below the threshold formula is shown [9]:

$$T(n) = \begin{cases} \frac{p}{1-p\left(r \, mod \frac{1}{p}\right)} & N \in G \\ 0 & otherwise \end{cases} \tag{7}$$

It should be considered that in the formula, *p* is the probability of becoming the CH and *r* is the present round. *G* is the set of those nodes that were the CH in the past *1/p* round. Consequently, if a node is chosen as the CH in round 0 it cannot be the CH in the next round. After becoming the CH, the node starts to advertise in the neighborhood and those nodes which received the message become cluster nodes based on some circumstances. Moreover, one compelling reason to save energy is utilizing the TDMA communications method which leads to avoiding the intra-cluster collision. Hence, a cluster member can send data to the CH only when it is awake and it is scheduled to do so. Another compelling reason to use clusters is that the CH aggregates data to minimize the number of data that must be sent to the sink or the BS and therefore energy consumption is reduced [34].

After selecting the CH, it starts to broadcast the advertisement messages to its neighbors and adjacent nodes receive the message. When a node is located between multi CHs, the node should decide which cluster to join based on the Received Signal Strength Indicator (RSSI) [9]. The GTS slots are restricted by the IEEE 802.15.4e standard, hence the number of nodes cannot exceed 7 inside the cluster.

In the final step, the CH creates a Time-division Multiple Access (TDMA) schedule and assigns the nodes their slot number. It should be noted that changing the CH in the same cluster does not affect the cluster formation and nodes continuously communicate based on the TDMA schedule and only the role of CH is switched among the nodes. In the next part, the simulation's details will be explained.

4.2 Network Simulation - The Pynet Simulator

In order to simulate the network, A simulator with more than 2,000 lines of code, was developed called "Pynet". It is based on *Simpy* which is developed on python 3.7. Pynet was developed because it was challenging to integrate an evolutionary algorithm with existing simulation environments, for instance, *cooja* and *omnet++* simulators require an integrated API for sending the superframe size and combinations and determine the remaining energy. Also, utilizing an integrated environment to increase the pace of progress on the DE algorithm phase was the reason to create an integrated simulation environment.

Simpy is a discrete-event based simulation engine package on Python that enables our simulation to act as a real simulation application and where nodes can behave simultaneously. There are numerous simulations based on Python such as *Pymote* [35] and *Pymote* 2.0 [36] which is an extension of *Pymote*. Both *Pymote* and *Pymote 2* have used *Simpy* as a simulation engine. Although they support energy models, these simulators are based on python 2.7 and cannot support new libraries.

Since proper MAC protocol can lead to a collision-free network [37], a superframe is designed based on 802.15.4 standard to utilize a clock that is built on Pynet to synchronize communications. To avoid inter-cluster communications, 7 GTS slots are employed and other communications use CAP slots in the superframe. In addition, the inactive period of time is used to enable sensor nodes to sleep mode to preserve energy. Although in networks, there are different mechanisms to send data, beacon and control packets. Also, it is assumed that data of each application is fit to one slot of the superframe and is sent in only one slot of time.

In Pynet simulation, they are sent based on the superframe structure. This also conserves energy in the network. Pynet is capable of supporting the below features:

- Multithread programming (each node works separately)
- Energy modeling
- Packet loss modeling
- Visual graphic of network topology

- RSSI modeling
- Superframe (MAC Layer- CSMA-TDMA)
- LEACH-C algorithm
- Sensor node modeling,
- Cluster modeling,
- Network configuration,
- Node to node communication,
- Logs and reports.

Packet Loss Model

To have a packet loss model in our simulation which is one of the important challenging parts for each wireless network routing is the Packet Delivery Ratio (PDR). Jacobsson et al. [38] claim that different packet sizes can affect the PDR. Hence, they generated packets with 15 or 16 different sizes and the error charts depict the 95% confidence interval between two devices in indoor non-line-of-sight (NLOS) scenarios. In all experiments, WLAN (IEEE 802.11), IEEE 802.15.4 standard, and *DASH7* (ISO/IEC 18000-7:2009) are employed [38] by utilizing the sky mote with *CC2440RF* chip. In Pynet simulation, the same packet delivery ratio is made based on [38] for CSMA communication. In the simulation, if a packet is lost, since the consumption of energy is related to packet transmissions, the lost packet will be re-transmitted resulting in more energy consumption. Communication between clusters (CSMA) rarely occurs so the energy consumption is fairly linear.

Energy model

In this simulation, the *Pymote* energy model is used [36] for the *Pynet* simulation. In the inactive part of superframe, the communication device goes to sleep mode with zero energy consumption. The energy configuration is shown below:

$$TR_{RATE} = 250\ kbps \quad transmission\ rate$$

$$P_{TX} = 0.084\ Watts$$

$$P_{RX} = 0.073\ Watts$$

$$tx - time = \left(\frac{packet\_size * 8.0}{TR\_RATE * 1024.0}\right)$$

$$power\ consumption = Tx\ power * Tx\ time \tag{8}$$

It means when a packet is sent by a node, that node consumes energy based on the packet size and time of transmission.

4.3 DE algorithm steps

In this part, the details of the algorithm steps will be discussed. Table 2 demonstrates the configuration of the simulation. As it is shown in Figure 7 the simulation scenarios included a network area of 300 m × 200 m [39] in which 23 sensor nodes are dispersed. In Figure 7, the blue nodes are simple nodes while the pink nodes are CHs. These nodes' positions are fixed and start with 2000 mJ of energy.

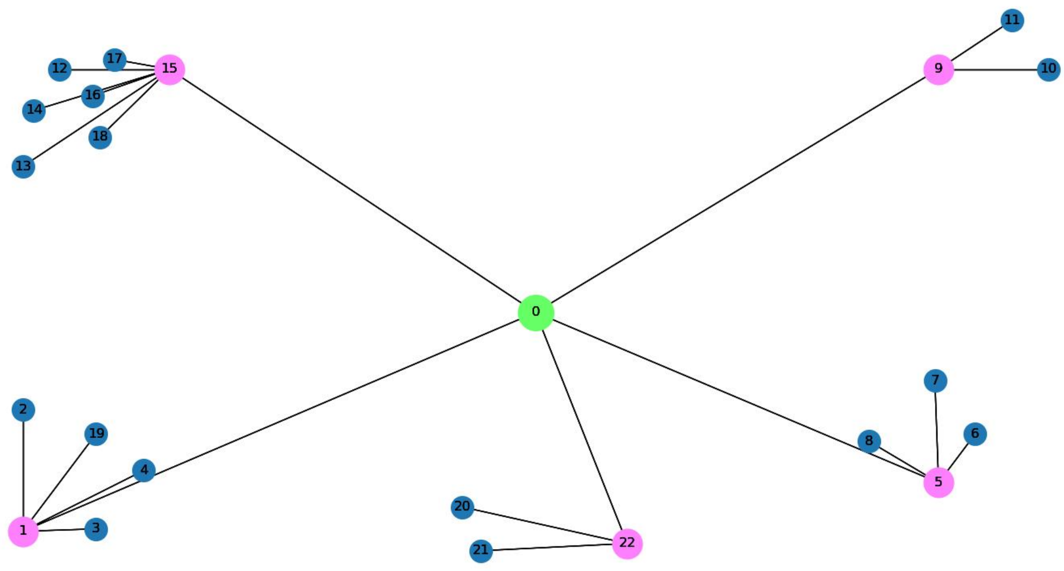

Figure 7 The network configuration

Table 2 Simulation configuration

Parameters	Value
Simulation	Pynet2
Number of nodes	23
Area Size	300 * 200 m
TX Range	70 m
Battery	2000 mJ

Also, Table 3 demonstrated the DE algorithm configuration and parameters for this DE algorithm execution phase.

Table 3 DE hyperparameters

Parameters	Value
Population size	100
Number of generations	31
Crossover probability	0.9
Mutation factor	0.8

After an execution with 50,000,000 units of time, data will be saved on a data frame structure and stored for analysis. In the next part, the outcomes will be demonstrated.

4.4 DE algorithm Phase Results

Based on the execution phase, 100 initial populations for first-generation and a total of 3,100 populations are generated to find the optimal result. In the figure, the brighter color of populations means more remaining energy. Figure 8 demonstrates the last 100 population of the DE algorithm.

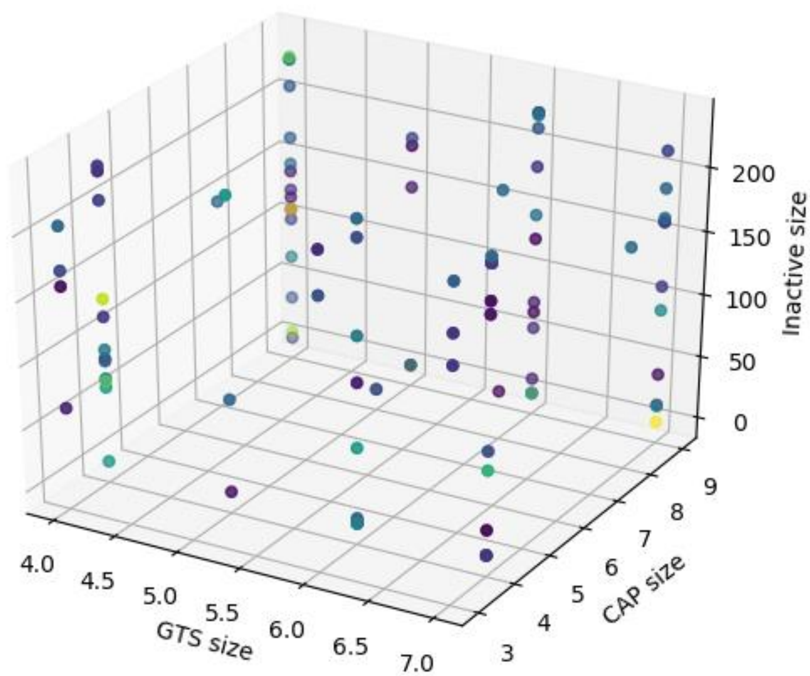

Figure 8 the population of the DE algorithm

The remaining energy distribution is shown in Figure 9. The y-axis is the number of population and the x-axis shows the range of remaining energy of all generations.

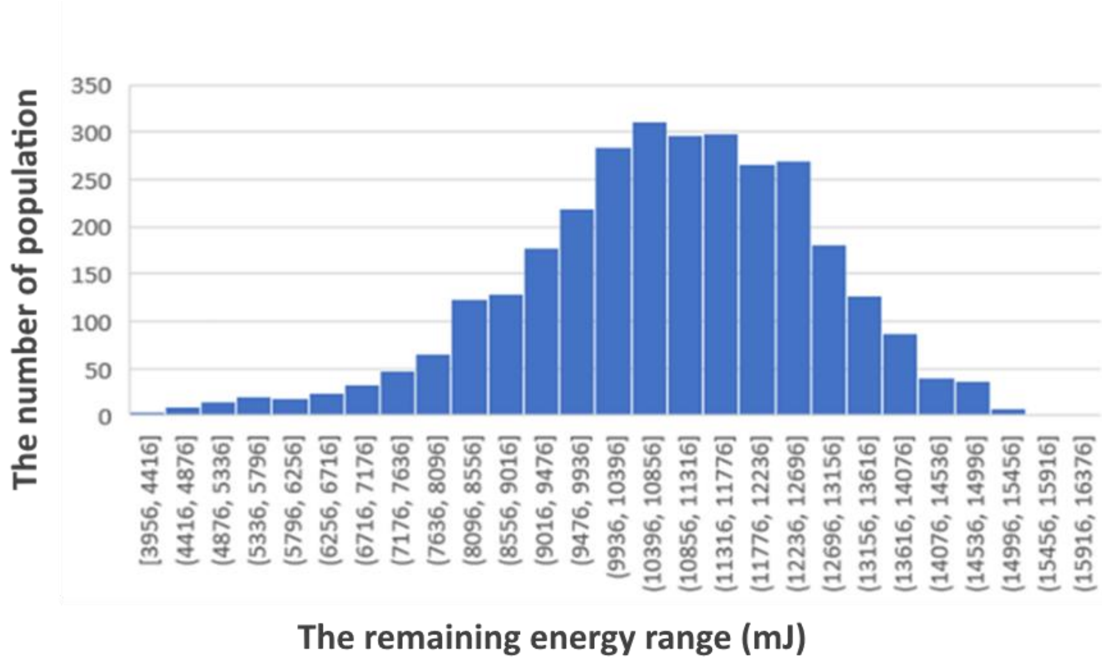

Figure 9 The remaining energy distribution based on chromosome population

Based on the results, the proportion of a single-superframe in comparison to the multi-superframe is shown below. In Figure 10, the occurrence of Multi-superframe emerged 2984 times while that of a single-superframe only 116 times. This is straightforward in terms of energy-saving since the multi-superframe structure enables only monitoring nodes, to be more likely to stay in sleep mode but in a single-superframe, each node must send data in every superframe.

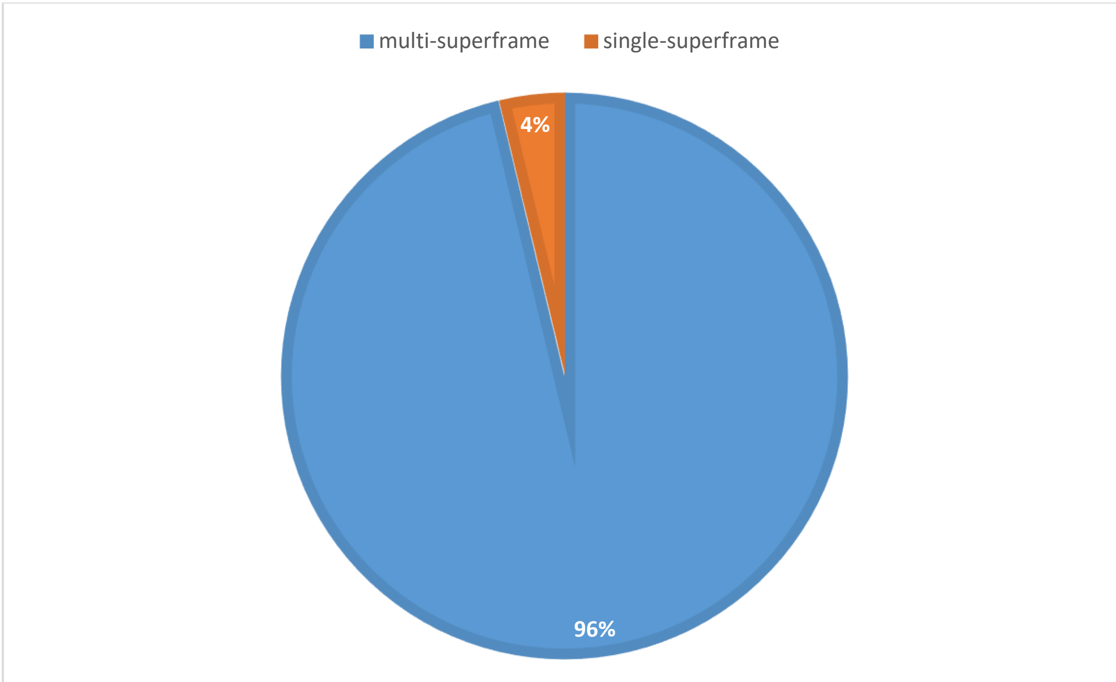

Figure 10 The proportion of single-superframe vs multi-superframe

Figure 11 demonstrates the advantage of using multi-superframes for communication. The figure shows that on average the remaining energy is higher for the cases where the multi-superframe is used over the single superframe. Based on the DE algorithm phase, the remaining energy of the multi-superframe structure can increase on average from 6824.473 to 10998.66 mJ.

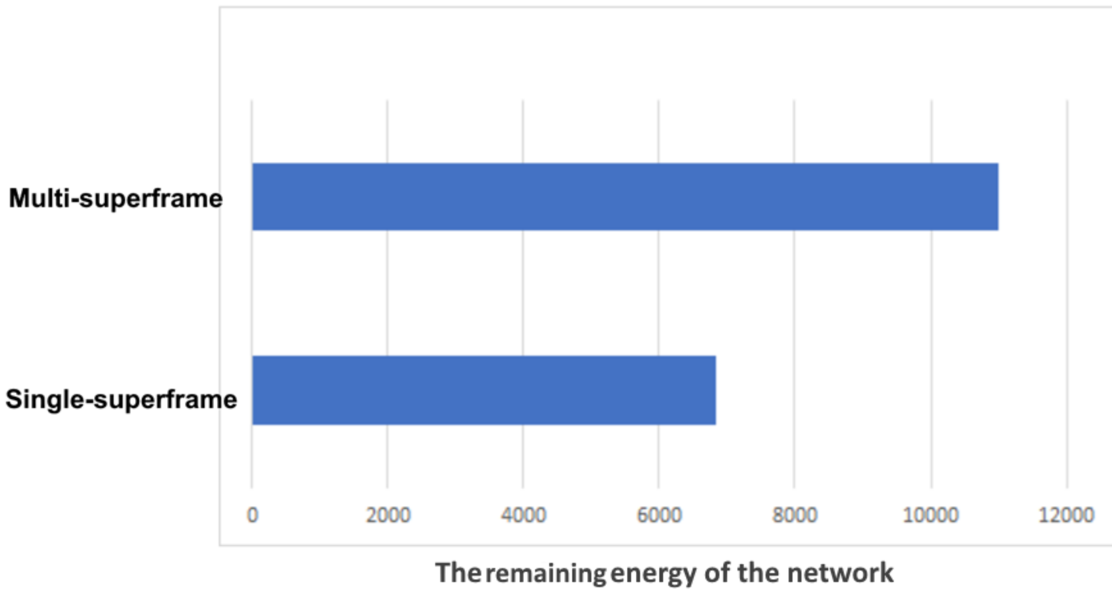

Figure 11 The remaining average energy of single-superframe vs multi-superframe

In terms of GTS slots picked by the DE. Figure 12, shows that there is no particular preference to any particular slot size as the remaining energy and the distribution of the chromosome population are roughly the same across the size of the GTS.

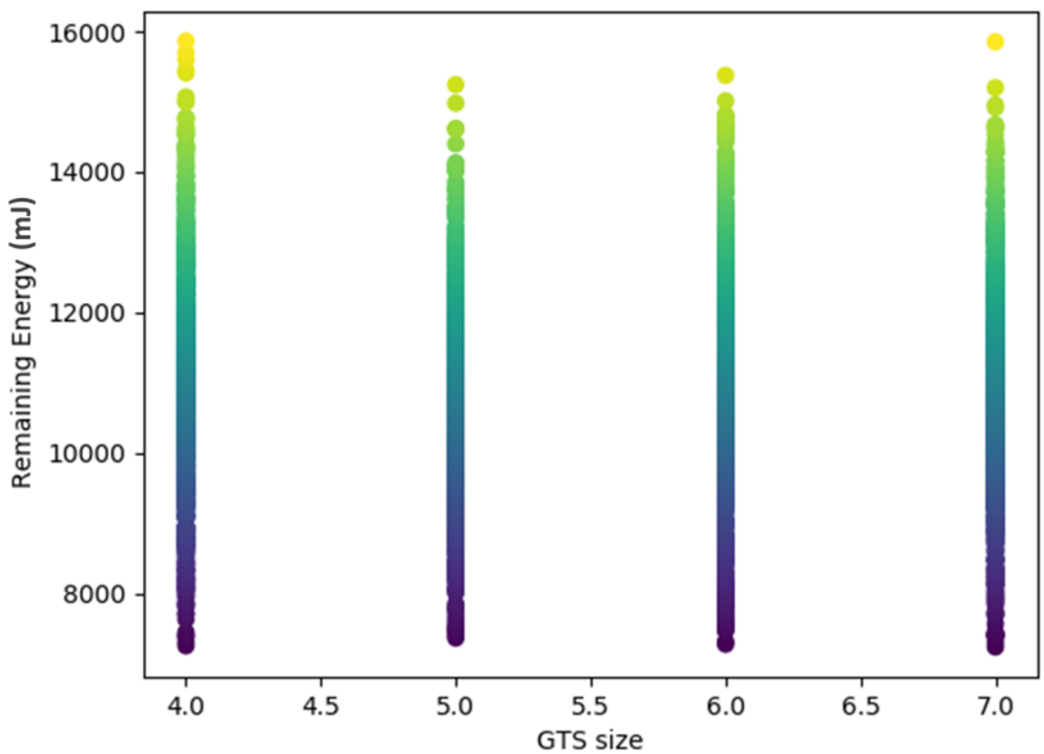

Figure 12 the GTS size of the population

On the other hand, Figure 13 is a view of the generations from the perspective of the CAP size. It shows that the best generations are more likely to have 3, 4, 8, and 9 values for CAP size. Based on the fitness function DE generates more values for CAP sizes of 3 and 4. Hence, these numbers have more density. Slot numbers 3, 4, 8 and, 9 conserve more energy in this simulation based on the observation.

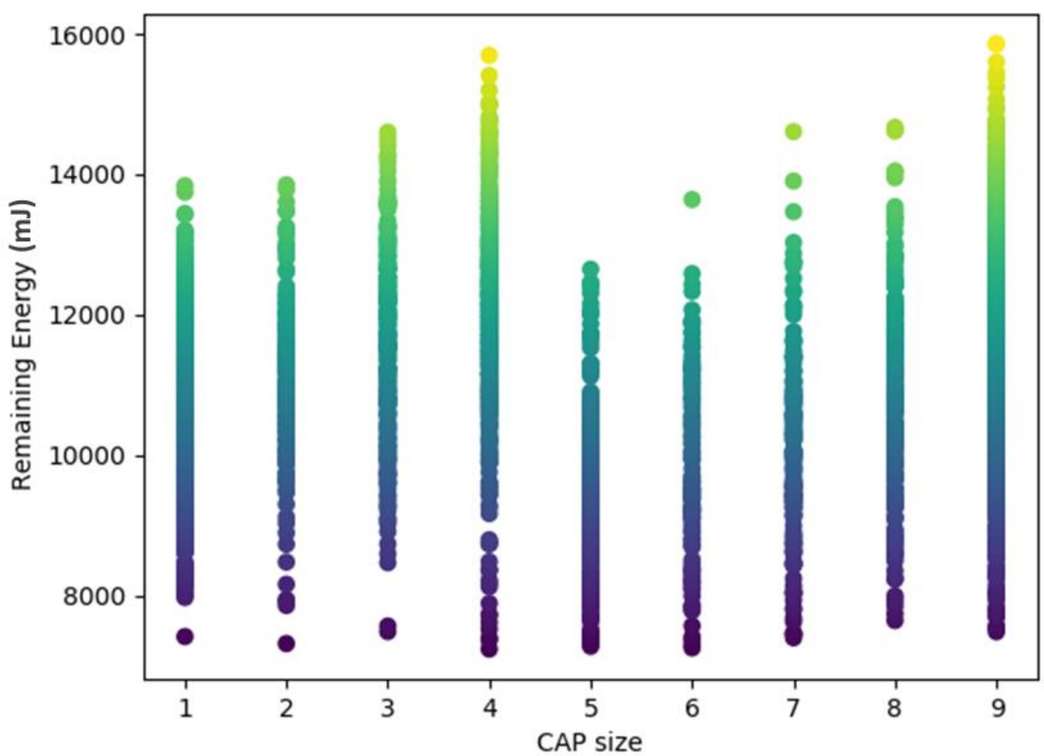

Figure 13 the CAP slots of the population

An interesting observation about the evolutionary algorithm is that the last generations of offspring lose their weak genes and a trend is seen how during the simulation the single superframe disappears after several generations and only the multi-superframe gene survives. Hence, in Figure 14 the multi-superframe structure is generated for the last generations.

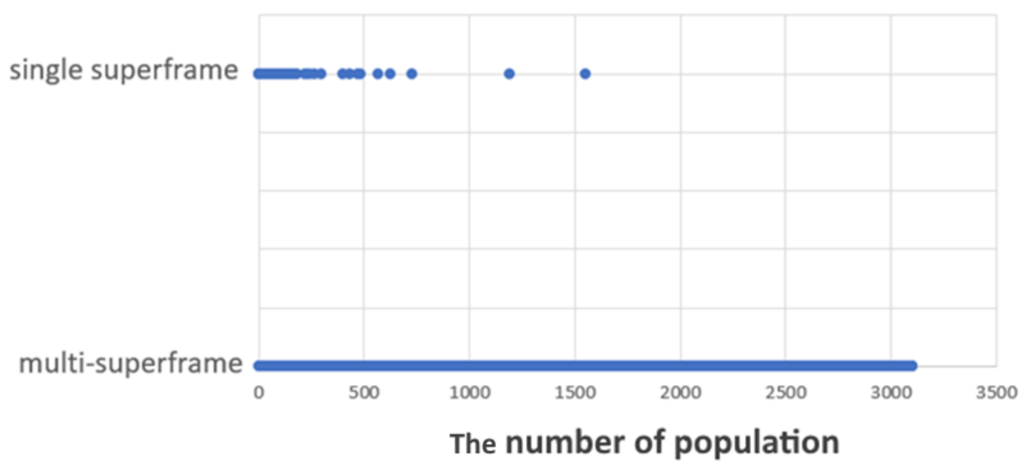

Figure 14 single-superframe vs multi-superframe genes

4.5 The Optimal Pareto Front

For multi-objective problem, there is no single optimal solution and the dominant solutions are considered as a set of solutions, called the Pareto Front. When a solution is not dominated by the other solution then it is a Pareto solution [40]. A solution is Pareto optimal, if it is impossible to boost a given objective without demeaning at least another objective. For example, in Figure 16, the solutions A, B, and C are Pareto optimal fronts while fitness function 1 (f1) must be minimized and fitness function 2 (f2) demands to be maximized. Hence, they cannot be dominated by each other while solution D is dominated by A, B, and C.

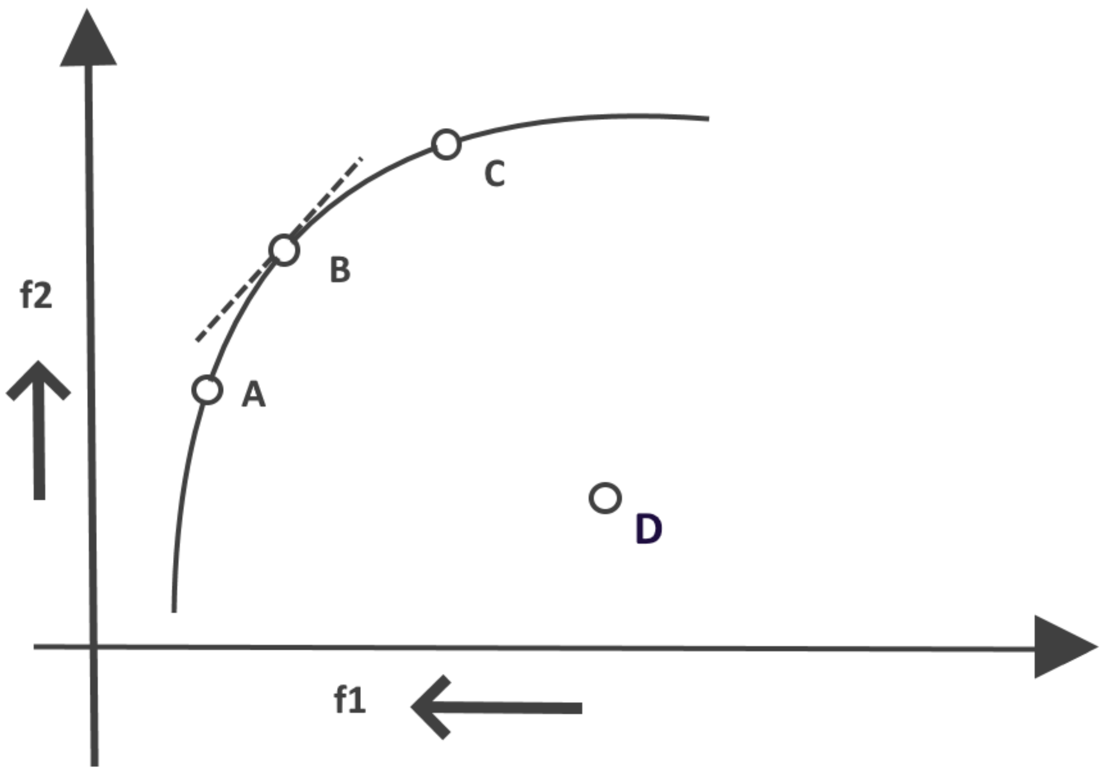

Figure 15 The Pareto optimal solutions

The optimal Pareto front of execution is shown in Figure 16.

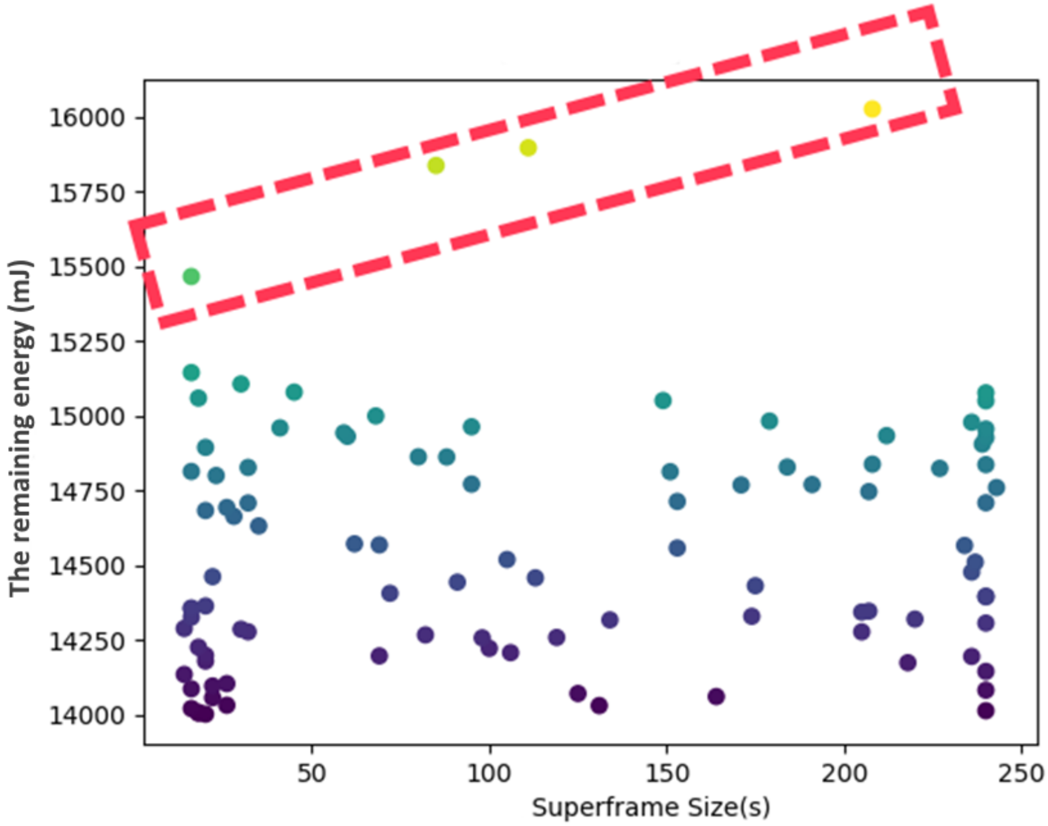

Figure 16 The Pareto front of superframes

Chapter 5. Sensitivity analysis of the DE

In this chapter, the sensitivity of the optimization method will be evaluated. This analysis takes place in two parts namely the sensitivity analysis based on the simulation time used to train the EA and sensitivity analysis based on different network configurations prior to the first node dying in the network.

5.1 Sensitivity to the Network's Configuration

In this part, time is not considered and the execution phase will be conducted with two different configurations of the network. In terms of configuration sensitivity, the results show that based on the different network configurations, the optimal solutions can vary from case to case. In Figure 17, there are two different network configurations are examined. The first one consists of only two clusters, while the second one consists of five clusters.

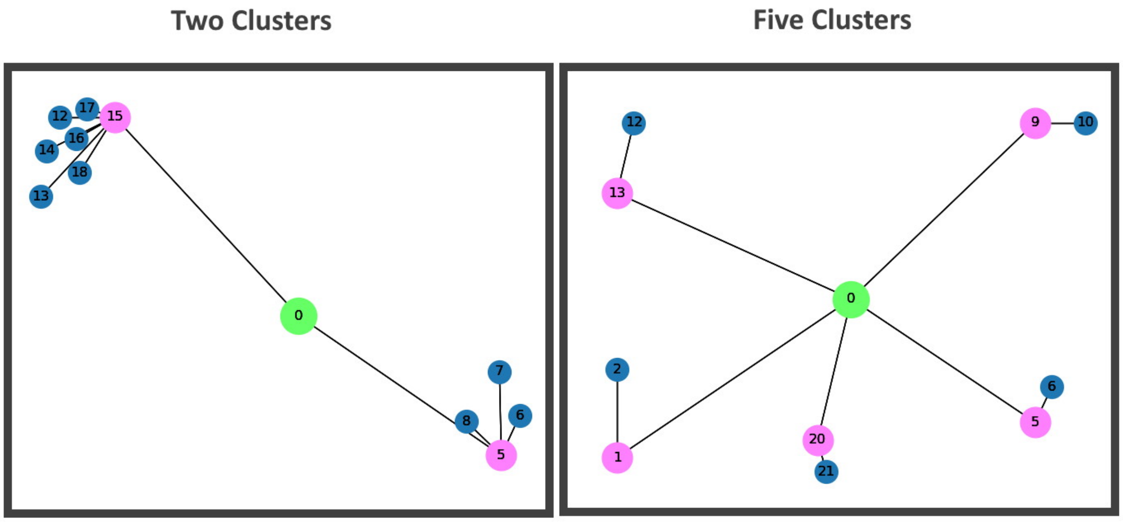

Figure 17 The Network configurations

In the first case, the network configuration is comprised of two clusters, and the Pareto front is shown in Figure 18.

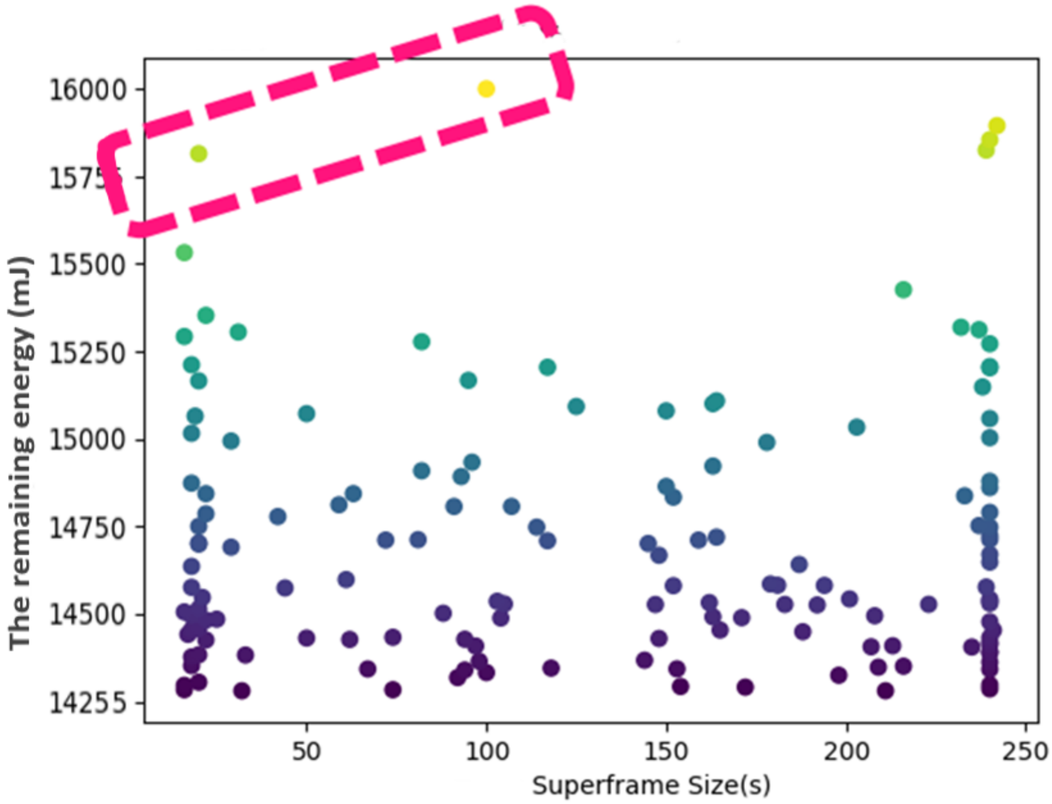

Figure 18 The Pareto front of two clusters

In the second case, the network configuration is comprised of five clusters with only one node inside each cluster to see the effect of a completely different network configuration on the proposed method. The Pareto front is shown in Figure 19.

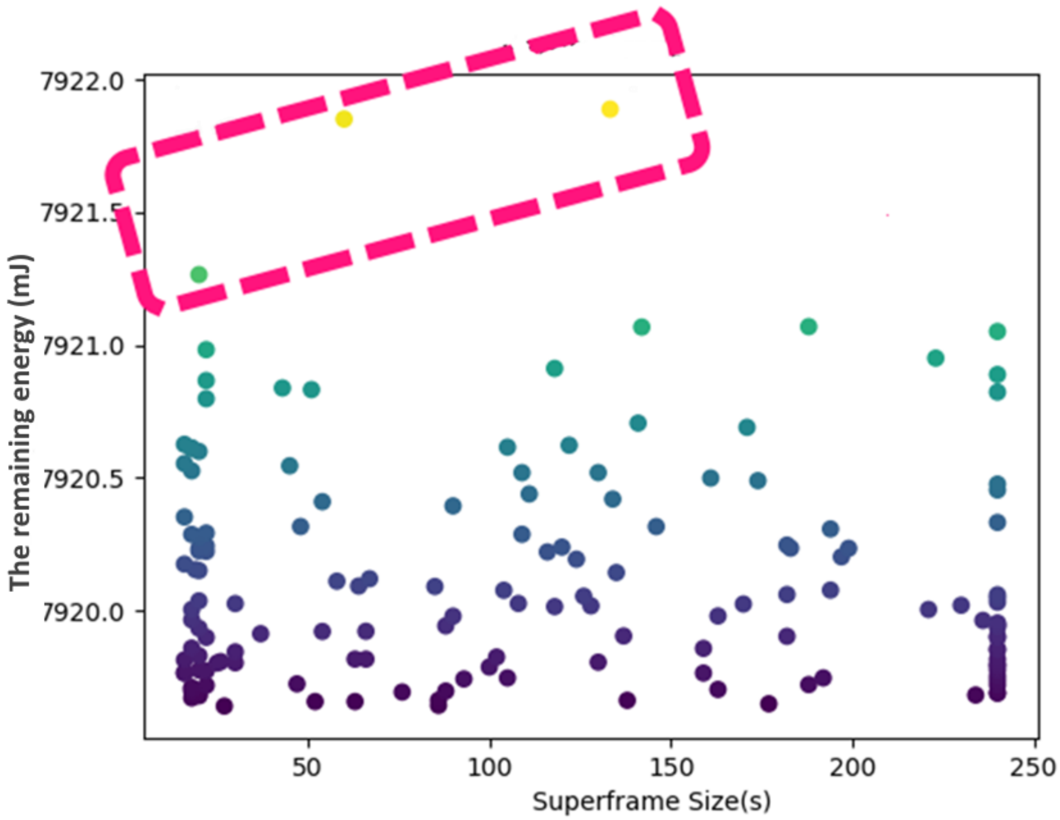

Figure 19 The Pareto front of five clusters

Based on those test runs, there is no correlation between proposed solutions and the network configuration. Hence, our proposed method is sensitive to network configuration since different network configurations lead to different results.

5.2 Sensitivity to the Simulation Duration Time

In another test run, it is determining the effect of simulation duration time on the robustness of solutions. The optimization sensitivity test was conducted a total of 7 different periods of time: 10,000, 50,000, 100,000, 500,000, 1,000,000, 10,000,000 and 50,000,000 unit of time. The expectation of the test runs is that the remaining energy decreases insignificantly over simulation duration time. However, in case of longer simulation duration time the node dies and changes the configuration of the network resulting in the diversity of results. As Figure 20 shows, the diversity of the remaining energy for all populations for the shorter duration of the simulation is denser, compared to the longer simulation durations. Hence, longer simulation durations have more diversity, and the solutions are less reliable. The reason for this is that the death of nodes results in different network configurations, hence, the remaining energy can vary in the execution phase results. Moreover, some clusters become disconnected because of the death of CH resulting in the isolation of other nodes. The distance of these nodes from the base station is too far and the signal is not strong enough to create the connection since their TX and RX ranges can not support long distances.

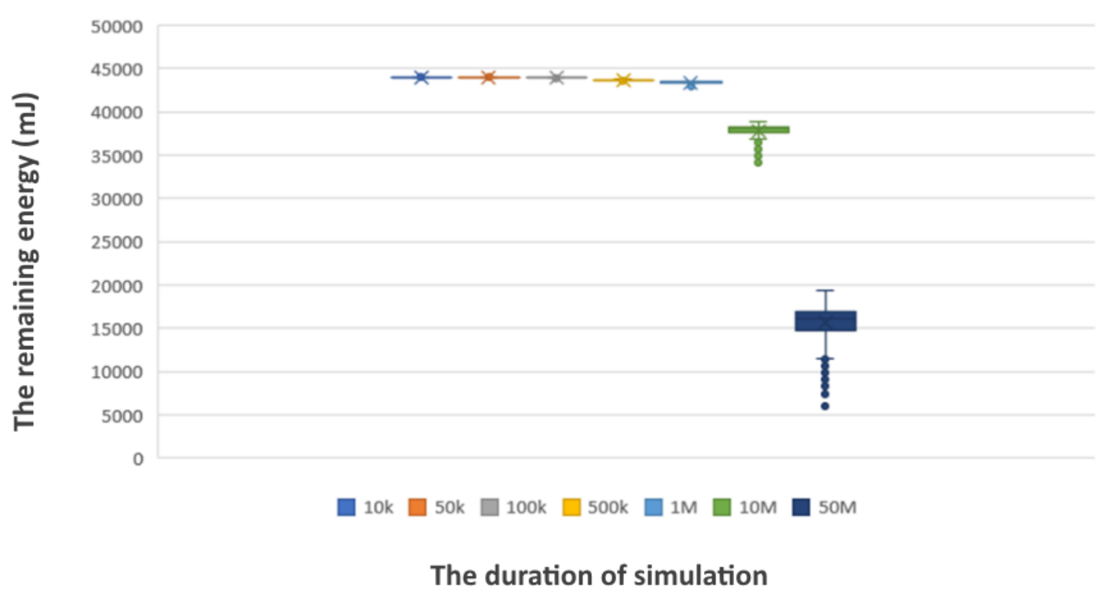

Figure 20 The remaining energy based on different simulation duration time and corresponding diversities

In terms of the data acquisition rate, Figure 21 demonstrates, that all the simulation duration phases generate superframe sizes between 16 to 240 seconds based on the IEEE 802.15.4e standard.

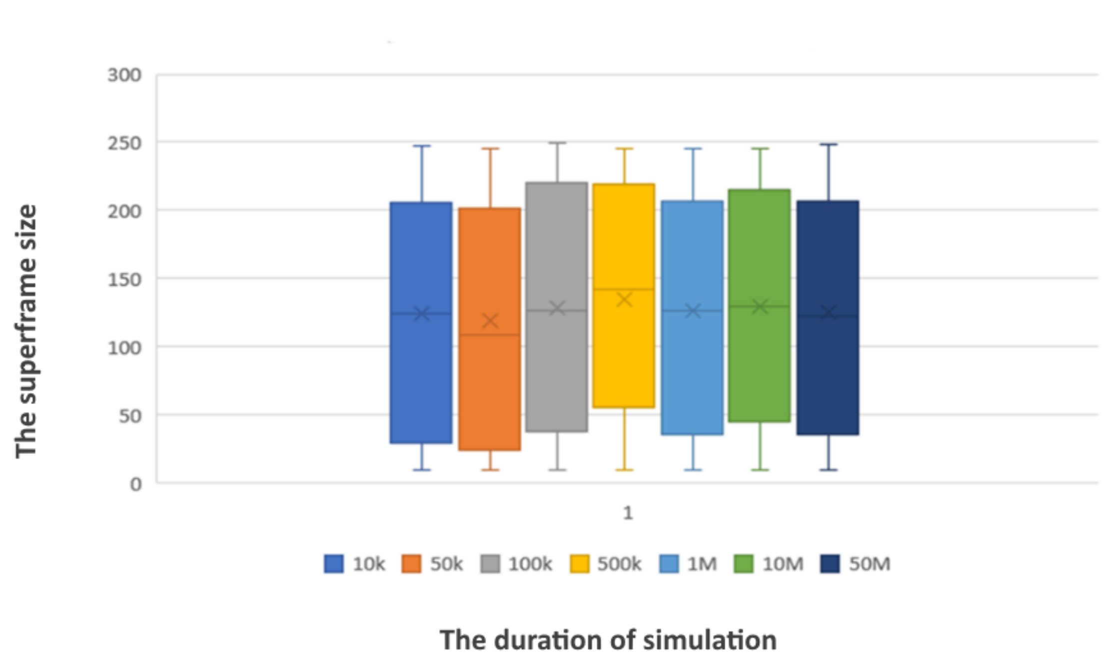

Figure 21 superframe's sizes based on different simulation duration time

As Figure 22 illustrates that as the duration of the simulation increases, many nodes will die leading to a change in the network configuration. A Box and Whisker Plot demonstrates data distribution through the quartiles by utilizing the 5 numbers of data. These numbers are the minimum, first quartile, median, third quartile, and maximum.

Since the network configuration changes, the solution can be more varied in terms of CAP slots. For example, although 500k has insignificant variation, a notable different pattern is seen in the 50M duration of time.

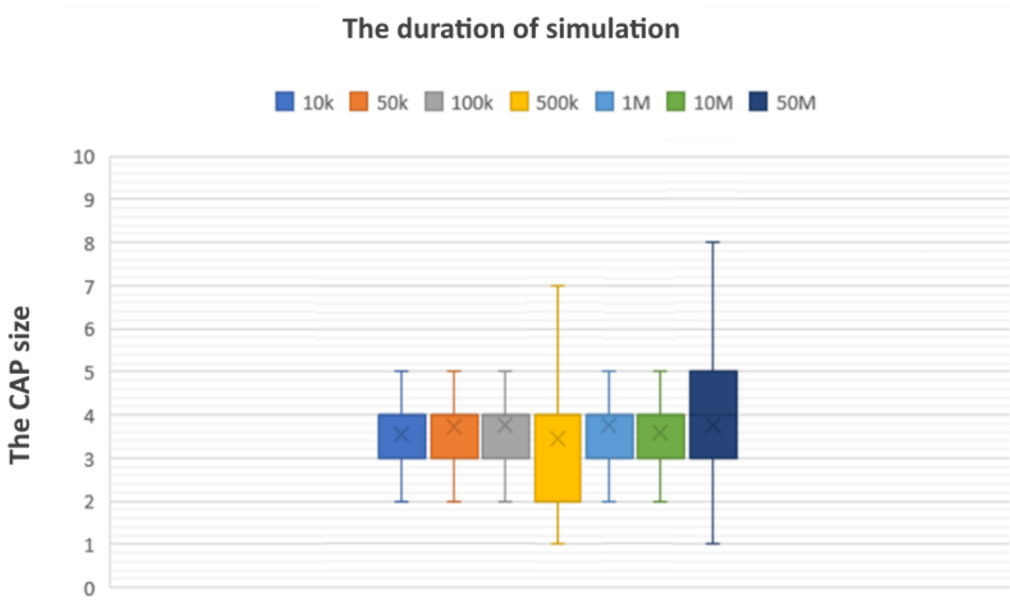

Figure 22 Sensitivity analysis for CAP based on different simulation duration time

5.3 Simulation Duration Time Sensitivity

The Execution phase was performed using two different simulation duration times, 50,000 and 100,000-time units, to determine whether the DE algorithm phase is sensitive to the simulation duration time. Due to the fact that the death of nodes leads to a change in the cluster formation and network configuration, hence, execution phase was conducted with durations of 50,000 and 100,000 units of time which is guaranteed that no nodes die.

In the first case with a 50,000 duration of time. Figure 23 demonstrates the Pareto front of 50,000 units of time, the result shows that the optimal solution is a superframe size of 240 with the configuration of GTS:7, CAP:4, Inactive:229, and MO:0 with the residual energy of 41670.52 mJ. When the data acquisition rate is not considered, the optimal solution is the solution with higher remaining energy.

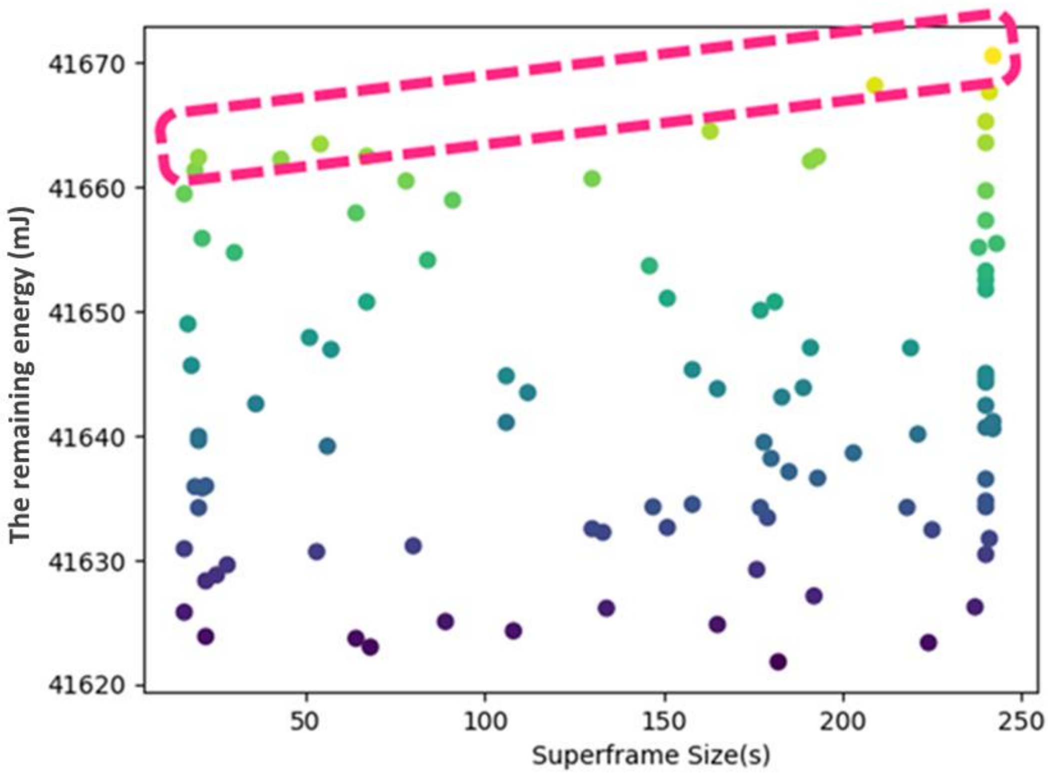

Figure 23 The Pareto front of the 50,000 units of time

In the second case with 100,000 duration of time, Figure 24 demonstrates the optimal Pareto front. The optimal solution is superframe size of 115 with the following configuration, GTS:5, CAP:4, Inactive:106, and MO:0 and residual energy of 39402.99 mJ.

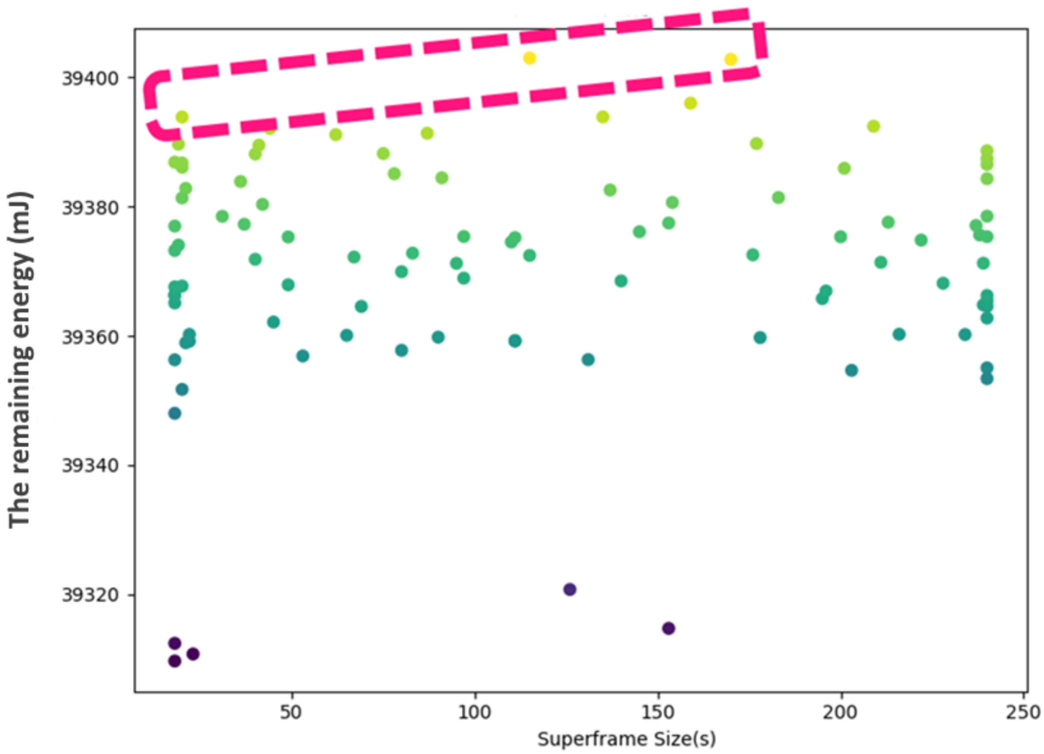

Figure 24 The Pareto front of the 100,000 units of time

Based on those test runs, there is no correlation between proposed solutions and simulation duration time. Also, the comparison between superframes' sizes and compositions for optimal solutions demonstrates that there is no stability in the results, as illustrated in Table 4.

Table 4 The superframes' comparison of the simulation duration time comparison

Duration	GTS	CAP	Single-superframe or Multi-superframe	Inactive size	Superframe size	Remaining energy (mJ)
50,000	7	4	Multi-superframe	229	240	41670.52
100,000	5	4	Multi-superframe	106	115	39402.99

Again, one observes that DE prefers to use a multi-superframe structure in new generations. Hence, the weak gene disappears after 31 iterations as it is shown in Figure 25.

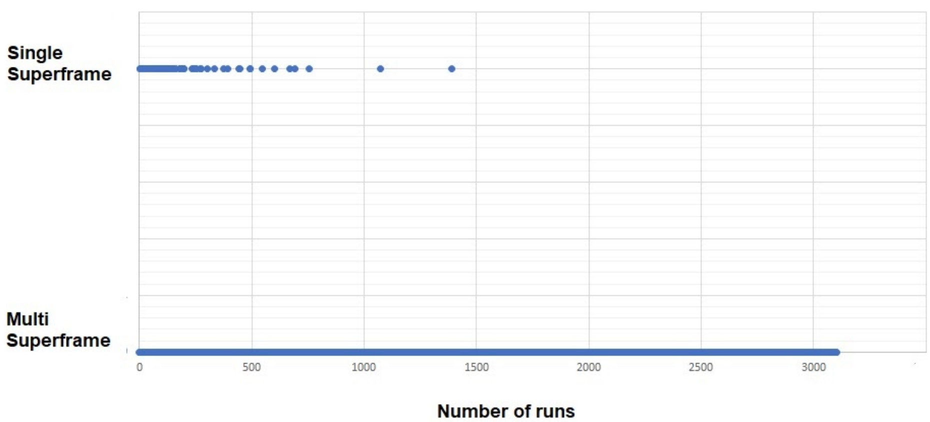

Figure 25 Multi-superframe gene

The sensitivity tests showed that the methodology and execution phase is sensitive to the network configuration and that there is no general solution for all problems or scenarios. It is therefore important to run the optimization phase under the conditions when the network topology is stable (i.e. all nodes are operational). For each unique WSN configuration, the optimization process needs to be executed from the beginning. In these experiments, the population generation took between 12 hours to 4 days (based on simulation duration time) executing on an environment that is set up as follows CPU: Intel Core i5-8250U 1.6 GHz; RAM: 8 GB; System: Windows 10.

Even though the DE algorithm results in a different Pareto solution for different simulation times the amount of energy consumed for solutions when the network is stable, are fairly consistent. Because the DE algorithm is a stochastic population-based search method resulting in different Pareto front solutions it is a challenge to determine an optimal simulation duration time when results are determined to be stable.

Chapter 6. Choosing an optimal solution from the Pareto front

In this chapter, a procedure is presented on how to leverage the Pareto front optimal solutions to pick one of these based on a particular set of sensing scenarios. One assumption is that the network is homogeneous, which means it consists of two types of nodes: one type is monitoring nodes and the other is emergency nodes. The idea of a multi-superframe structure enables the network to work simultaneously with two applications without conflict or resending the beacon packets. The monitoring nodes can send the data every other superframe while the emergency nodes demand to send data every superframe.

In this scenario, there are two types of sensing applications: 1) A Fire alert system with a 1-minute data acquisition rate, 2) Monitoring system with an 8-minute acquisition data rate. It should be noted that the data rate acquisition is related to superframe size. Hence, based on these two applications, an optimal solution should be selected.

Since the Pareto Front is a set of solutions, the main unsolved problem is selecting the optimal solution. To remedy this, the system sorts the data acquisition demands of applications from the lowest to highest frequency in terms of the data acquisition rate. The application that demands higher frequency can act as a constraint and filter the solution.

Since the emergency application demands a 60-second data acquisition rate, the first solution that supports these criteria is selected as an optimal solution for the whole network. In other words, the solution with a 1-minute data acquisition rate or less can meet the needs of the application with demands of the 8-minute data acquisition rate, the shorter solution is selected as the optimal solution is circled in Figure 26.

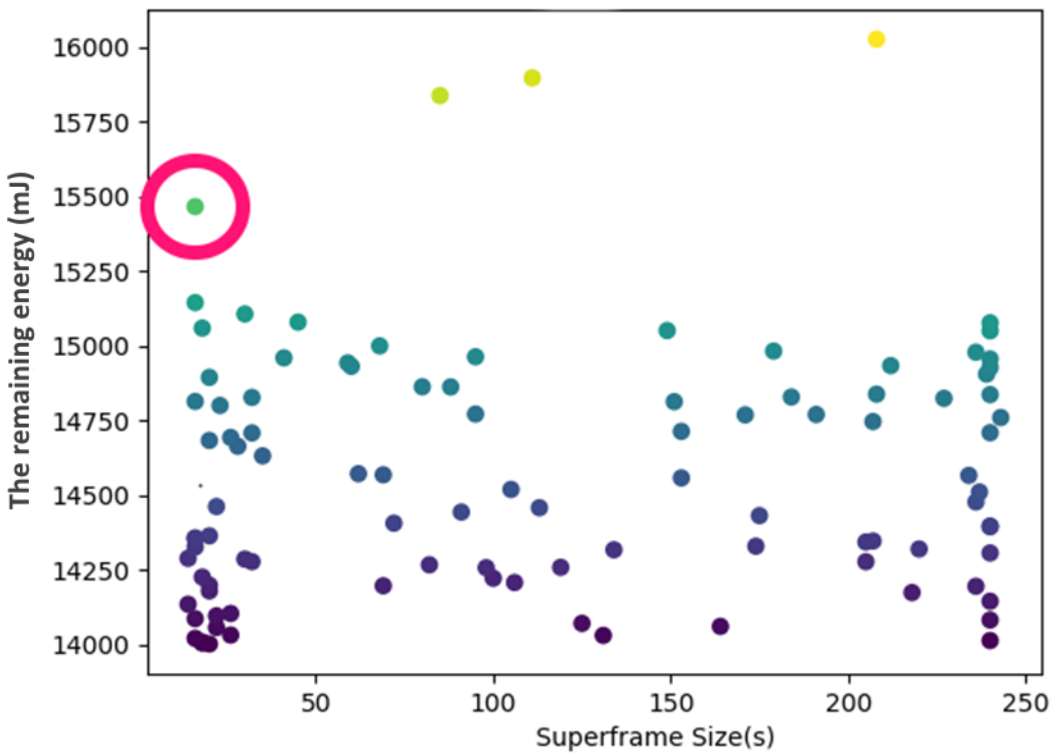

Figure 26 the solution selection from the Pareto front

Since the optimal solution is selected by solution selection, from that time onwards, the appropriate superframe size and composition are set into the configuration file of the network simulation. The network will work with this configuration until a new emergency application shows up and changes the solution selection method. In some cases, based on the situation, a new optimization process will be conducted from the beginning to find new optimal value to respond to the new demand of the application.

6.1 Comparison with previous works

In this section, a comparison is made between the results presented in this thesis to the superframe sizes suggested in previous works. This is not a simple exercise because the other approaches in the literature review section considered only the BO and SO components of the superframe that makes the problem simpler. They mainly benefit from the exhaustive search while in this thesis evolutionary algorithm is utilized and the CAP slots, GTS slots, and inactive slots are also considered.

For example, on one hand, Salmaya et al. [25] found the optimal combination of (BO, SO) between {(6,6) and (8,8)}. Also, Khalifeh et al. [22] demonstrated the optimal solution is when both the beacon order and superframe order values are equal to 3. When comparing the results to the studies with equal SO and BO, the inactive part does not exist. Thus, by omitting inactive slots, the previous results consume more energy compared to the proposed model.

On the other hand, Kim et al. [21] evaluated BO and SO (4,3) ratios for the optimal solution. Also, Similarly, Lee et al. [24] created a priority-based algorithm for adaptive superframe adjustment and GTS allocation (PASAGA) in the IEEE 802.15.4 standard. They showed that BO = 4 and SO = 3 is the optimal solution. The reason why their work is selected for comparison is that they benefit from the inactive part since the BO and SO are not equal. Hence, their work is adapted to our simulation to evaluate the differences and results with the existing approach. The challenging part of the conversion of their superframe is that they implied BO and SO standard and it is mandatory to convert it into CAP, GTS, and inactive parts. With reference to section 3.1, *aBaseSuperframeDuration* is calculated.

$$symbolTime = 0.016\, ms$$

$$aBaseSlotDuration = 60$$

$$aNumSuperframeSlots = 16$$

$$aBaseSuperframeDuration = aBaseSlotDuration \times$$

$$aNumSuperframeSlots \times symbolTime$$

$$aBaseSuperframeDuration = 60 \times 16 \times 0.016 = 15.36\, ms$$

$$SO = 3$$

$$SD = aBaseSuperframeDuration \times 2\text{^}SO$$

$$SD = 15.36 \times 2\text{^}3 = 122.88\, ms \text{ active part}$$

$$BO = 4$$

$$BI = aBaseSuperframeDuration \times 2\text{^}BO$$

$$BI = 15.36 \times 2\text{^}4 = 245.76\, ms$$

$$Inactive = BI - SD = 122.88\, ms \tag{9}$$

Since they did not consider GTS and CAP slots separately, the maximum 9 as CAP slots and the maximum 7 for GTS slots are considered for comparison purposes. For adapting their superframe structure to the Pynet simulator, SD (active part) is divided into 16 slots, hence, each timeslot is equal to 7.6 ms. Also, the inactive part's duration is 122.88 ms, hence, the inactive part has 16 slots as well. Their superframe is converted to [GTS:7, CAP:9, Inactive:16, MO:1].

Using a simulation time of 10,000,000 units, the simulation demonstrates that the results from using the DE model not only performs better than previous papers in terms of energy consumption but is also superior regarding the size of the superframe. The simulation illustrates, after the same duration of time, the remaining energy of the solution (SO = 3, BO = 4) was 35453.6 mJ while our method remained at 37225.207 mJ, demonstrating a 5% better result in terms of energy. Hence this works shows how evolutionary algorithms can aid in order to save energy by manipulating superframe size and composition and to benefit from multi-superframe structure regarding different application demands. Consequently, this work illustrates that an evolutionary algorithm can adequately be trained to find a set of optimal superframe schedules and composition for clustered WSN operating under diverse data acquisition rates.

Chapter 7. Conclusion and Future work

An Optimized Multi-Superframe Scheduling for Clustered WSN (OMSS-WSN) is proposed that leverages a differential evolution (DE) algorithm. The DE is employed to fulfill the objective, to maximize network life under adequate data acquisition rates. An integrated environment simulation with an evolutionary algorithm is made, called "Pynet".

There are several values of the current work. It benefits from the evolutionary algorithm, multi-superframe structure and, clustering formation regarding applications to illustrate the effect of optimization on energy consumption. It is also demonstrated that a Multi-superframe structure can conserve more energy than the use of a single-superframe.

The main challenges to current work were: first, a superframe can be defined by Beacon Order (BO), Superframe Order (SO) and it is found difficult to map cluster formation to the current method since we are oblivious to the sizes of GTS and CAP slots. Hence, the challenge was converting another system superframe to a new simulation. The second challenge was, there is no correlation between proposed solutions regarding the network configuration and the time duration. Moreover, the last challenge was in multi-hop simulation with a greater number of nodes, distributed LEACH can handle a bigger network better than LEACH-C.

Also, instead of using SO and BO sizes that are typically used in other works, this thesis focuses on GTS slots, CAP slots, and inactive slots. This is more effective in terms of energy conservation because the GTS slots are collision-free slots and are bound to the cluster formation.

It is demonstrated that there is no particular preference for any particular GTS slots size while for CAP slots, the numbers 3, 4, 8 and, 9 conserve more energy in this simulation based on the observation.

Moreover, the adoption of a multi-superframe structure can conserve more energy than the use of a single superframe. The final important factor is that the applications' data acquisition rates are considered in the optimization process as well.

The OMSS-WSN provides a set of solutions, "Pareto front" based on the constraints and goals. Two application scenarios are presented that demonstrated how the Pareto front solution could be applied to the network. With comparison to the state-of-the-art, superframe optimization techniques, it was demonstrated that the OMSS-WSN approach reduced energy consumption with an optimal superframe size. The simulation showed that our proposed model not only outweighs 5% of the previous works in terms of energy. Interestingly, evolutionary algorithms are more likely to use a multi-superframe structure to maintain more energy.

7.1 Suggestions for Future works

The following areas also have been identified for the extension of the work presented in this thesis.

This approach can be evaluated with different evolutionary algorithms like a genetic algorithm (GA) and particle swarm optimization (PSO) instead of DE. The performance and the results of these algorithms can be evaluated and compared.

It is also recommended to determine the effect of optimized cluster formation on superframe optimization in future work. Since this work used static network, optimized cluster formation can be applied first then superframe optimization can be integrated on the top of the first optimization. Also, different clustering algorithms other than LEACH can be compared to the proposed method. Finally, the impact of two optimizations on the results could be investigated.

Moreover, since Pynet is built for specific scenarios and situations, hence, an improvement of simulation can be useful for feature works. For example, it can be more user-friendly, it can support different clustering and optimization algorithms.

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