Parallelly Implemented Hybrid Multi-Objective efficient persuasion of Coverage and redundancy Programming model for Internet of Things in 5th Generation Networks using Hadoop

Thesis Submitted for the Award of the Degree of

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In

Electronics & Communication Engineering

By

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2023

DECLARATION

I, hereby declared that the presented work in the thesis entitled **"Parallelly Implemented Hybrid Multi-Objective Efficient Persuasion of Coverage and Redundancy Programming Model for Internet of Things in 5th Generation Networks using Hadoop"** in fulfillment of degree of Doctor of Philosophy (Ph.D) is outcome of research work carried out by me under the supervision **Dr. Krishan Kumar**, Professor of Electronics and Communication Engineering, Lovely professional University, Punjab, India. In keeping with general practice of reporting scientific observations, due acknowledgements have been made whenever work described here has been based on findings of other investigator. This work has not been submitted in part or full to any other University or Institute for the award of any degree.

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CERTIFICATE

This is to certify that the work reported in the Ph.D thesis entitled "**Parallelly Implemented Hybrid Multi-Objective Efficient Persuasion of Coverage and Redundancy Programming Model for Internet of Things in 5th Generation Networks using Hadoop**" submitted in fulfillment of the requirement for the reward of degree of Doctor of Philosophy (Ph.D) in the department of Electronics and Communication Engineering, is a research work carried out by **B. Ravi Chandra**, 42000067, is bonafide record of his original work carried out under my supervision and that no part of thesis has been submitted for any other degree, diploma or equivalent course.

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ABSTRACT

In this paper, we suggested a parallelly implemented Hybridized Mayfly and Rat Swarm Optimizer method utilising Hadoop for improving IoT coverage and node redundancy with huge nodes. Our goal is to increase the lifespan of IoT by successfully resolving the coverage issue via massive nodes, hence spreading the IoT lifespan. The NS2 tool is used to simulate the suggested technique.

We begin by offering an overview of how IoT applications confront new opportunities, difficulties, and the development and diffusion of 5G networks. We also discuss the expansion and popularity of 5G networks, how IoT submission confronts new potential and problems, and how sensor nodes in IoT frequently need constant power supplies. As a result, extending the lifespan of IoT devices is a critical issue. The IoT coverage problem, which was formerly an NP-complete problem, handles tough massive-node scenarios that are routinely beyond the resolving power of existing algorithms.

We then concentrate on the algorithms in use, which must normally reserve a collection of other answers. A tremendous number of plausible solutions are required to complete the solving process in large-node configurations. The operation will fail because time will run out before the computation is completed. As a result, the algorithm must fulfill three critical requirements in order to address the IoT coverage problem in massive-node scenarios.

To begin with, the technique must be capable of compressing the size of the issue while yet completing the calculation in a timely way. The coverage challenge for the Internet of Things is likewise a multi-objective programming problem. Third, internal algorithm enhancement is necessary so that the solution process can advance fast to useable results. As a result, the algorithm should evaluate network coverage, node redundancy, and the influence of the current functioning node configuration on the upcoming configuration.

Following that, we used Hadoop to create a parallelly implemented Hybridized Mayfly and Rat Swarm Optimizer method (MOP-Hyb-MFRS-IoT-5GN). Initially, parallel operation divides the IoT coverage issue using large nodes into several smaller issues in order to reduce the problem scale and fix it using parallel Hadoop. The coverage problem is optimised here by observing mayfly flying and mating behaviour. The pursuing and attacking actions of rats are used to solve the redundancy problem. Then, from the crucial nodes, ideally choose the non-critical nodes.

Finally, simultaneous execution successfully overcomes the IoT coverage issue by deliberately spreading that IoT lifespan.

If this work is to be compiled for this thesis, performance measures such as IoT Lifespan radius against Computation Time, IoT Lifespan radius vs Energy Efficiency, IoT Lifespan radius vs Lifetime, and IoT Lifespan radius vs Remaining Nodes are studied. The suggested MOP-Hyb-MFRS-IoT-5GN approach is then compared to current methods such as parallel MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN-IoT-5GN.

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Every step I take in life is done to honour my father, late Mr. B Chennaiah. My goal is to continue in my father's footsteps and ensure that the heritage endures forever. My Mother Mrs. B Nagendramma is a continual source of inspiration for me, and she has shaped who I am today. She is to credit for all I've accomplished. I don't know how to thank my mother, whose love and care have been my greatest strength. I could not have finished my study without my mother's understanding, support, and patience. Mrs. B Keshavi and Mrs. B Madhavi, my elder twin sisters, deserve special recognition for their constant moral support throughout my courses, Mr. G. V. Ramana and Mr. G Rajesh, my in-laws, for their unwavering support and encouragement.

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF SYMBOLS

D	Dimensional vector
V	Velocity
Dx^{T+1}	New Position
Dx^{T}	Current Position
Vx^{T+1}	Current Velocities
x	Space Seeking
Z^{T}_{xy}	Identical Mayfly's Location
P_{bestxy}	excellent posture
Q_{bestxy}	desirable male mayfly position
g	Target Value
C_p	Cartesian distance
G	density factor
G_{max}	number of iterations
G_{min}	lowest number of iterations
$\vec{P}_a(U)$	rat's location
$\overline{P_b}(U)$	Ideal Solution
$\overline{P_a}(U+1)$	Revised Location
i	number of iterations
d	proportions
$Max_{iteration}$	Maximum number of iterations
W_s	width of the shell
W_H	width of the head
I_D	Inner diameter
C_L	length of the cylinder
$D1$	first shaft's diameter
$L2$	second shaft's diameter
L1	first shaft's length
P	pinion's number of teeth
X	monitoring region
nxm	Grid
r_i	number of i^{th} sensor nodes
R	sensor node set
D_j	Sub division of nodes
$S_{cov}(D_j)$	Matrix count
$S_{redudancy}(D_j)$	rate of redundancy
$M_{fesiable}$	number of potential solutions
U_{in}, U_{out}	Input, Output energy

CHAPTER -1

IoT AND WIRELESS COMMUNICATIONS IN 5th GENERATION

CHAPTER -1

IoT and Wireless Communications in 5th Generation

1.1. INTRODUCTION

The development of 5G wireless technology is one of the most difficult and interesting research areas. It will open the door for creative wireless architecture and clever services. The Long-Term Evolution (LTE) will fall short of the requirements for several remote access, high bandwidth, high throughput, and high speed, and won't be effective either. low disturbance and high quality of service (QoS). 5G is the most emerging tool for addressing these concerns. The difficulties and objectives that different communications teams are trying to achieve in 5G IoT devices are thoroughly examined in this chapter. Today's society places a great demand on higher data rates for cellular communications with a fast internet connection, which also plays a key role in the digitalization of society and the globe as well as smart economic growth.

Existing wireless technologies, such as 3G and 4G, are unable to support the demands of 5G wireless standards and cannot be utilized for long-distance communication or low power wide area (LPWA) technology. Long Range (LoRa), an IEEE 802.15.4-based specification (ZigBee), Wireless Fidelity (WiFi), Low power wide area networks (LPWAN) including SigFox, and Narrowband-Internet of Things (NB-IoT) are the only ones that can readily access the unlicensed or unused frequency band where 5G wireless technologies for the Internet of Things are likely to operate [84]. Narrowband-Internet of Things (NB-IoT) has three usage modes: independent, inside the zone, and guard band, each with a specialized application. New Radio (NR) technology is cognitive, employing the independent mode to reuse spectrum, in-band to effectively utilize frequency band, and guard band to make use of unused resource blocks [81-83]. Mobile users are currently in the millions, with an estimated 25% annual growth rate, and are predicted to reach 2 trillion by 2030. As is well known, one of the key developments in creating a smart world has been wireless communication [85]. The Enhanced Mobile Broadband (eMBB) and enhanced machine-type communication (eMTC) vital communications all employ 5G radio broadcasting technology ultra-reliable low latency communications (URLLC). These techniques will allow communication between devices to devices (D2D), between devices and everything (D2E), and between machines to machines (M2M), as well as Internet of Vehicles (IoV), and between the Internet of Things

(IoT) [86]. All those communication systems must include low PSME (Price, Space, Mass, and Energy) enabled. Systems from 1G to 4G rely on orthogonal multiple access. Multiple orthogonal accesses are ineffective for 4G due to this. 5G cellular networks provide an increase in frequency above 4G systems, making it simpler to attain broader bandwidths.

It is first required to comprehend how architecture, auxiliary technologies, and security measures have evolved in order to have a standardized framework for 5G.

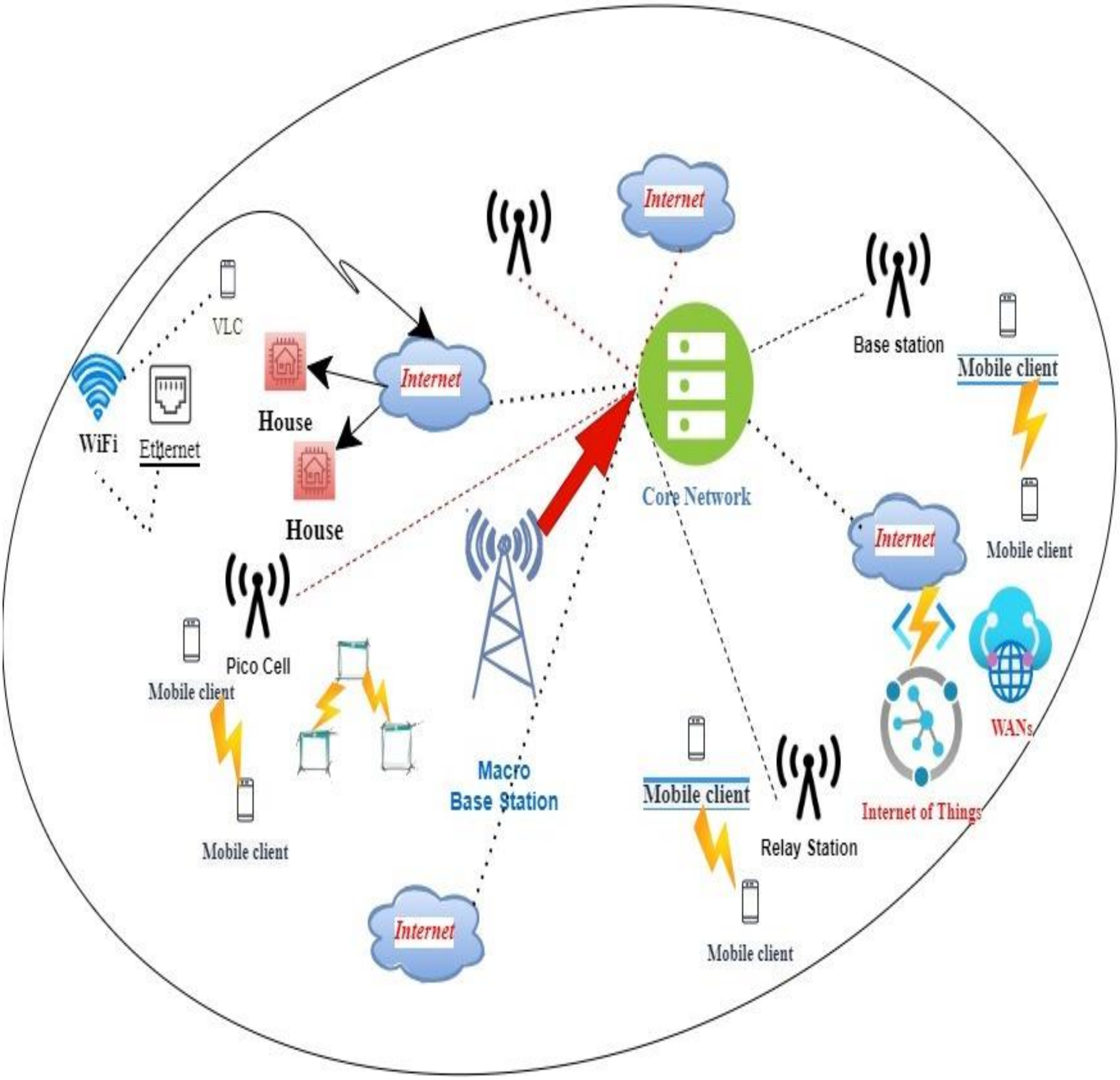

Figure.1.1: 5G Functional Structure

1.1.1. A New Generation of Cellular Networks

Following are the requirements for 5G networks, according to an association:

- Enhanced information bandwidth of 1 Gb/sec to many employees on the same employee level, higher spectral accuracy over 4G, faster, improved signaling efficiency, coverage, and a considerable decrease in legacy compare to (LTE).
- From the introduction of the Norwegian cellular phone, the 1st generation structure, in 1982, the latest cellular generation has appeared about every 10 years.
- The formal debut of the first "2nd Generation" network took place in 1992, while the "3rd Generation" technology followed suit in the year 2001.
- The first fully IMT-advanced compliant 4G systems were developed in 2012. Since the R&D projects for the 2nd Generation Code Division Multiple Access (CDMA) and 3rd Generation Universal Mobile Telecommunications System and International Mobile Telecommunications-2000 (UMTS and IMT-2000) levels officially began about ten years ago, 4G system development began in 2001 or 2002.

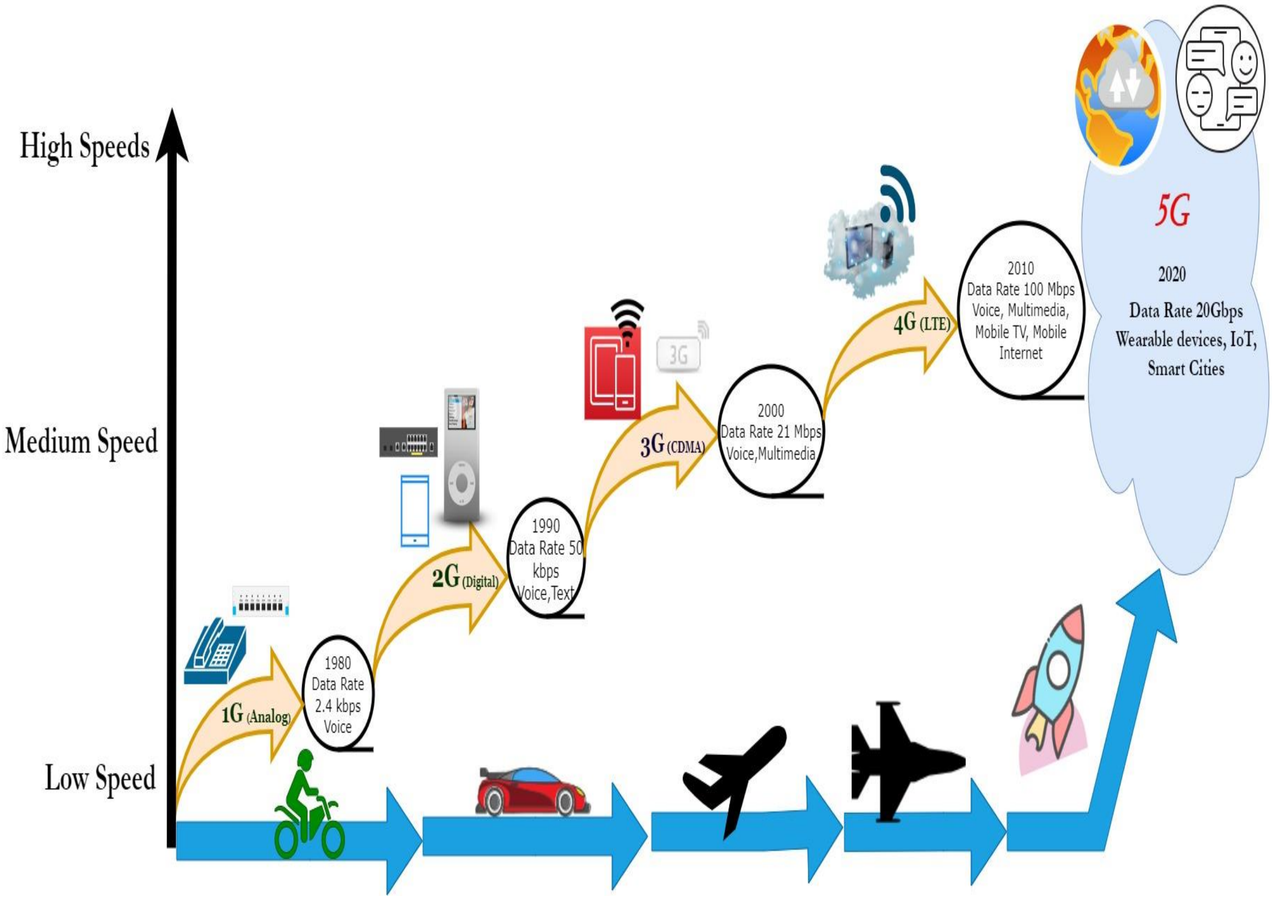

Figure.1.2 Wireless Technology Developments

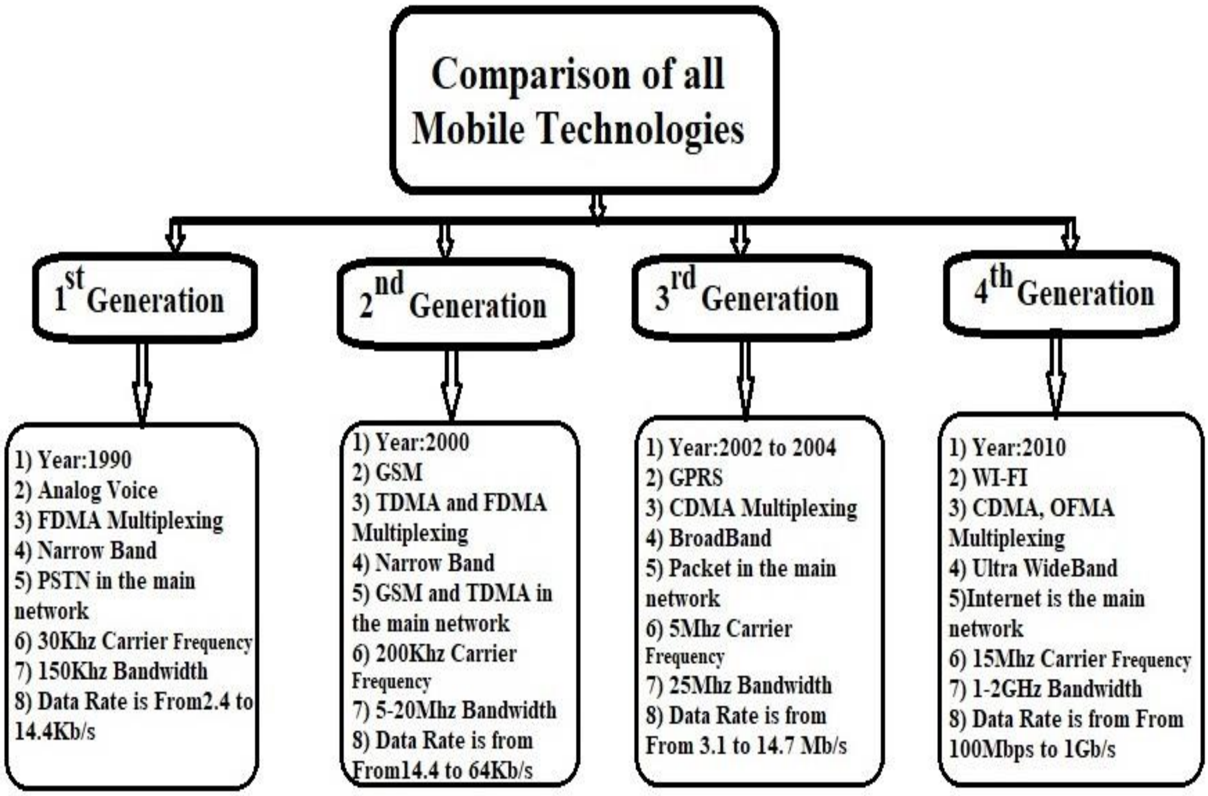

Figure.1.3 Comparison of Mobile Technologies

Beam Division Multiple Access, sometimes referred to as BDMA or Filter Bank Multi-Carrier, abbreviated as FBMC Multiple Access, is an extremely cutting-edge access technology that makes it straightforward to transition from 4G to 5G. The idea of BDMA methods is made evident when the ground station connects with the cell locations. For unrestricted multiple connections to the cell sites, each cellular unit is given an oblique beam that may split using the BDMA approach based on the location of the cell sites. This improves the operation of the system and acts as the main channel of communication.

1.1.2. Drawbacks of 4G

The drawbacks that 4G cellular networks cannot effectively overcome are:

1. battery issue
2. Complicated hardware.
3. Network security problems.
4. 4G services are still not widely available.
5. Different handsets are required.
6. High power consumption.
7. Low cost.

1.1.3 Challenges of 5G

The progression from 1G to 4G technologies has revealed several difficulties in the design of the network and physical layers as well as their various application areas. 5G challenges are mentioned below.

1. Data transfer rate of 1 to 10 Gbps in network topologies: Data transmission should be ten times quicker than it is now.

2. Response time > 10ms: The delay must be 10 times less than that of LTE networks.

3. Increased bit rate and frequency effectiveness: MIMO antennas and millimeter wave technology can be used to achieve 5G technologies' high-speed requirements., and cognitive radio enables users to access commercial and non-commercial spectrum bands, which can result in good transmission.

4. Low price: Low-cost installation of devices and sensors should be a part of IoT.

5. Additional linked gadgets: A network will link around 1.2 trillion IoT devices.

6. Better battery lifespan: As gadgets become smarter, power consumption increases and energy storing and rechargeable batteries become increasingly important [39].

7. Reduce energy use by almost 90%: Energy consumption in 5G technologies may be reduced by deploying green technologies that are efficient in huge connections and high rates of data.

According to present developments, it has become accepted that 5G cellular networks need to tackle the aforementioned difficulties that 4G cannot adequately resolve. Such as larger efficiency, high information speed, lowest Levels of delay, massive device connection, lower costs, and consistent service providing quality.

To overcome the above challenges, a fresh concept for the construction of the There is now a 5G mobile communication design that can differentiate between inside and outside layouts. This planning approach will help to mitigate the loss brought on by contact through the walls of the structure. The scattered array of antennas, which are spread geographically and comprise numerous tiny units or are made up of dozens or even hundreds of antenna units, will be supported by the use of large-scale (MIMO) technology, according to the scheme or plan. Since MIMO systems now use either two or more towers, the notion of massive MIMO systems, which has been presented, principally puts stress on the utilization of the benefits of big array antenna components in terms of substantial acoustic gains.

The term "5G" refers to improvements achieved in the field of mobile communications in its fifth generation. These consist of packet-switched transceivers with broad coverage, high maximum output at millimeter waves (10 mm to 1 mm), operating between the frequencies of

30 GHz to 300 GHz, and having the ability to transmit data at a rate of 20 Mbps across a distance of up to 2 km.

A new network is largely required to support the growing number of internet-connected devices, There are several applications that no longer require 4G since they require a lot of bandwidth to work effectively. While 5G is expected to use extraordinarily high bandwidth in the 30 GHz to 300 GHz range, Lower than 6 GHz frequencies are used by 4G networks. Future connectivity demands will necessitate higher data rates, and 5G will make this possible with maximum downstream and internet speeds of up to 20 Gbps.

1.1.4. Advantages and Disadvantages of 5G

A range of features provided by future 5G technology is beneficial to all sorts of customers, especially students, specialists (specialists, technologists, educators, local governments, regulatory entities, and so on), and even the common person. The 5G Design Nanocore [3] is depicted above.

A) Advantages:

- 5G technologies offer a variety of advantages, some of which are outlined below.
- High-resolution bi-directional shaping with large bandwidth.
- The capability of integrating all channels onto a unified system.
- Better efficient and successful.
- Technology facilitates subscriber supervision tools for quick reaction.
- Will most probably provide a substantial quantity of projection data (in Gigabit), with capability for over 60,000 users.
- Easy to manage with elder generations.
- A solid technology base to support a variety of alternatives (including private networks).
- The ability to provide a consistent, uninterrupted, and continuous worldwide connection
- As smart gadgets that can interact with cell devices become increasingly prevalent in human life, more applications incorporating artificial intelligence (AI) will emerge [10].

B) Disadvantages:

After being researched and designed to handle every wireless signal difficulty and problem in the mobile industry, 5G technology suffers from the following downsides owing to worries about security and the overall lack of technical innovation in most places.

- **Limitation of Coverage:** Though 5G technology is billed as having the fastest speeds, its availability in just a few places across the world with 5G antennas is one of its limits. Despite worldwide firms and governments attempting to provide 5G coverage in as many places as possible, the introduction and deployment of 5G will take years due to the high cost of testing, trialing, and setting up 5G towers.
- **Weak Upload Speeds:** Despite its capacity to have quicker download rates, experts anticipate that the 5G technique will have slower upload speeds than 4G and 4G LTE. This is another disadvantage of 5G technology.
- **Battery Damages:** Another disadvantage of 5G technology is that it weakens cellular devices by depleting the battery and shortening its lifespan. So yes, just a few companies have released 5G-capable smartphones. While 5G gadget development is ongoing, experts say the technology is proven to be a stumbling block for 4G devices, since it frequently causes battery damage.
- **Interference with Airport and Flight Operations:** In January of this year, numerous airlines, including Air India, delayed flights to the United States as the country's telecom carriers attempted to roll out 5G services. According to the US aviation authorities, one of the top causes of flight cancellations was technological interference with aircraft operations. Although this problem has not been seen in other countries where 5G services have been deployed, it is another restriction of 5G technology.
- **Cyber security Possibility:** Another disadvantage of 5G technology is that it raises the risk of hacking, compromising cyber security. Additionally, since the connection procedure is not encrypted, 5G-enabled devices are more vulnerable to data theft and cyber-attacks.

1.2. INTERNET OF THINGS (IoT)

The Internet-of-Things (IoT) is the fusion of the Internet, sensors, RFID, and intelligent things. IoT may be summed up as "things belonging to the Internet" that provide and enable access to all information from the actual world. It is anticipated that thousands of devices would be connected to the system, necessitating a massive network distribution and the conversion of raw data into useful insights. IoT holds the greatest potential for technology today, but there is still a need for a cutting-edge mechanism that can be seen via the Internet of Things. The Smart Semantic framework is used for the first time in this design to contain the analyzed data from sensor networks.

In the coming years, IoT in the 5G network will change the game. The future of wireless networking is a network design that enables information sharing and is accessible to everyone, anyplace, and at every moment. IoT will soon have a big impact on how we live our lives. For the development of IoT devices, a contemporary wireless network architecture is required. Beyond 4G, several significant expectations must be met, including those for more capacity, faster data rates, lower latency, and better data security during transmission. Future IoT applications will find it challenging to handle such orthogonal multiple accesses.

It is expected that 5G will operate as the IoT eco-backbone system when it launches soon and that 5G-enabled technologies will provide a sustainable building for continuing growth. The Internet of Things will be the ideal use case for 5G. A system that can enable massive volumes of data transfer effectively and at extremely high bandwidth is needed as the IOT grows in popularity. Increased capacity, better data rate, and lower latency are some of the main criteria that need to be met for next-generation IOT devices shortly. The creation of 5G, the upcoming generation of wireless mobile communication technology, promises to satisfy the requirements of complex IOT architectures.

The initiation of 5G Internet will result in a wide range of communication kinds, data rates, energy usage, and safety and privacy concerns. IoT development across 5G mobile networks is primarily powered by the anticipated deployment of a large number of devices that demand high data rates. To make the system intelligent, the portable subsystem has Conceptual value-based information and conceptual logic. using wireless sensors, RFID, and 6lowpan, this study discusses internet-oriented applications, services, visual aspects, and problems for the Internet of Things.

Most of procedures and tools are utilizing the growing Internet of Things technology, which enhances people's quality of life and makes it easier to access a variety of information and services. By utilizing some of its capabilities, the Internet of things (IoT) is a service that can meet many forms of demand. "a technique that works well for a variety of tasks, for instance services provided in machine modelling, publication, control, analytical and identification [1]. IoT has achieved in removing other nearby systems because of their bright future and ability to make things simple to assess and analyze diverse sections [2]. In light of this assumption, an appraisal is crucial. Following Figure.3 shows the functioning of the Internet of Things.

1.2.1 IoT Equipment

An IoT device often referred to as an endpoint, can be thought of as a piece of technology that collects data while keeping an eye on a certain target. This is accomplished by deploying sensors that enable the collection of information on the relevant factors, such as location and other information of multimedia [13].

Each device in the system has a unique identifier called a unique identifier (UID), which may be used to identify the source of any particular data [14]. The internet of things (IoT) was created as a result of the fast development of new technology, as well as the easily integrated of wireless communication, sensors, and other devices and radio frequency identification (RFID). IoT, therefore, meets both the demands of the city's industrial sector and its people's comfort [15].

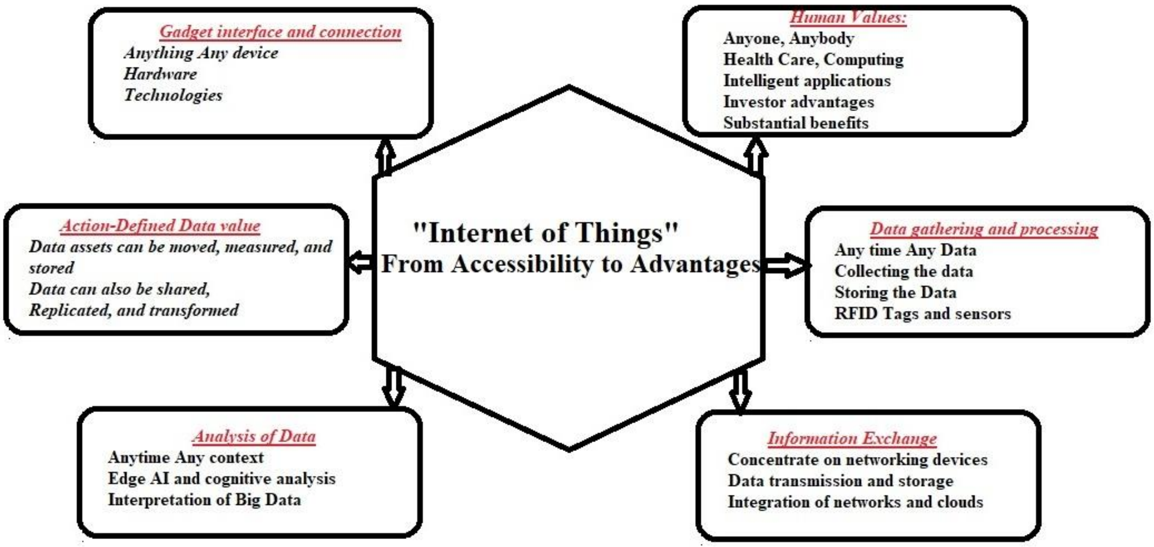

Figure.1.4 Schematic of IoT functioning

1.2.2 IoT Network

In today's world, the Internet performs the above responsibilities, and the solution is the network required to transport information across huge distances with low effort. "Now, the internet has expanded substantially quicker than any other technology and has been accessible everywhere"[16]. Because of this innovation, it is rather simple to read an article that was published in another country. Several methods for transmitting information have been developed in light of the sharp growth in demand.

In terms of the technology for the Internet of Things, A tool that could help with communication development is 5G. "The arrival of 5G is imminent, and IoT will take centre stage. as IoT devices would represent a substantial portion of the 5G network," this technology, can meet considerable traffic needs in network information [17]. This is a plan for utilizing these two technologies to meet the demand for the most effective, secure, and quick communication possible [18]. Another obstacle to creating extensive IoT applications is the lack of available spectrum [19].

1.2.3 Security

Security is one of the most important elements of any technology. Given that the information obtained is crucial and confidential, it is fundamental to the development of any technology. The security of this technology is on par with that of any monetary transaction. The use of blockchain technology is therefore a fascinating concept that can guarantee data security, message integrity, content integrity, and privacy. Data collection and transmission privacy and security that is directly tied to the users' life are now one of the possible dangers to IoT devices [20].

Blockchain is a cryptography method that encloses a link of informative units with a key known only to the last node. It helps with information transmission and device certification. In the same vein, the IoT and blockchain combo provide us the assurance that the data flowing from every piece of equipment inside a corporation is accurate and verified. This is accomplished by attaching a physical auditory to the apparatus, and the latter is configured to incorporate the business's and the apparatus's respective signatures, creating unique information. The unchangeable record of transactions involving industrial assets is made possible by blockchain. As it does not correspond to the other units in the link, information about updated blocks is not delivered to the record book.

1.2.4 IoT Cloud

The Internet of Things (IoT) proposes the total integration of various "things" and to create a clever link between people and objects around them, the internet will serve as the foundation of the communication system. As a vital part of the Internet of Things, the cloud offers crucial application-specific services in a variety of application domains. A lot of IoT cloud service companies are already stepping into the market to utilize relevant and customized IoT-based solutions. Although these IoT clouds have a substantial potential contribution, no typical thorough comparison study inquiry has been found in academic databases. Significant IoT cloud architectures in light of their capacity to handle a range of service domains, including data processing, utilities for analysis, installation, tracking, visualization, and research. It is a duty of storing, managing, and preserving the content blocks it receives with each flow of data coming from the devices. The assessment centers are entrusted with providing the users with assessments or findings on the data that was sent from the PCs to the cloud. Due to its ability to store and transmit important data from many research fields, the cloud is also the technology's most commercially viable component. This gives third-party businesses a thorough understanding of how the research subjects' enduring traits might be beneficial.

1.3. DEVELOPMENT OF THE INTERNET OF THINGS

A close study of these events shows two critical IoT pillars that require further explanation: "Internet" and "Things." This notation is used to refer to a wider range of entities, such as smartphones, sensors, people, and any other component that is conscious of its sense and can interact with other units, providing access to anyone at any time and from any location, despite what it might seem like if every device that can connect to the Internet falls under the "Things" category. This indicates that items must be reachable at all times, regardless of location.

The internet of things (IoT) is distinguished as "a machine-to-machine (M2M) and device-to-device (D2D) connectivity, providing the data collecting that can enable new technologies and shed information on analytical performance [2]. The Internet of Things (IoT) is a network of interacting static and moving objects, including devices with transmission, modules for sensors and actuators that linked together online [3]. A group of physical elements that are capable of responding to each other independently is referred to as the "IoT" [4].

IoT is characterised as "internet-connected embedded systems that can be upgraded and adapted to changing demands on demand, important information can be quickly obtained from remote geographic areas, and fault diagnosis and system restarts can be improved and cost-effectively by not having to send out technicians to remote sites" [5]. "IoT links sensing devices to the Internet to exchange information," [6]. The Internet of Things (IoT) is a worldwide ecosystem of information and communication technologies that [7], aims to link every kind of device (thing), at any time, and anywhere, to the Internet. "The IoT contains a numerous sensor nodes with insufficient handling, backup, and battery capability,"[8].

Radio-frequency identification (RFID) was once the main technology driving the development of the IoT. Nevertheless, as technology advanced, Bluetooth-enabled gadgets lesser focus has, however, been paid to the distinct qualities and demands of the IoT, including adaptability, diversity support, thorough interconnection, and real-time data retrieval [9–12].

1.3.1 IoT Structures

The core elements of the Internet of Things (IoT) include contextual event processing, network infrastructure, remote support initiation, and sensing devices. The Internet of Things (IoT) envisions a unified network of sentient items and humans who can operate them (if necessary), all of which are capable of universal and omnipresent communication.

Interconnectivity between entities is a crucial prerequisite when talking about a distributed system and the Internet of Things is an excellent example. Consistency is regarded as the most important structure feature in the IoT, and comprehensive system architecture for it must ensure the faultless operation of its components as well as connect the real and virtual worlds. To do this, failure recovery and scalability design must be well thought out. Additionally, given that mobility and periodic location change have evolved into crucial elements of IoT systems with the rise in smartphone usage, the current design must have some degree of flexibility to manage creative interconnections throughout the overall network.

Reference models and architectures provide a high-level overview of the whole underlying system; as a result, IoT has an advantage over other architectures in that IoT offers a better and higher degree of abstraction, which subsequently conceals implementation details and particular limitations. IoT Structure where shown in the following figure.1.4.

1.3.2 Network Standards

IoT may be seen as an amalgamation of several networks from a network and communication standpoint, such as mobile generations 3rd Generation (3G), 4th Generation (4G), Code Division Multiple Access (CDMA), etc., Wireless Local Area Network system (WLANs), Wireless sensor networks (WSNs), and Mobile Ad Hoc networks (MANET) [21].

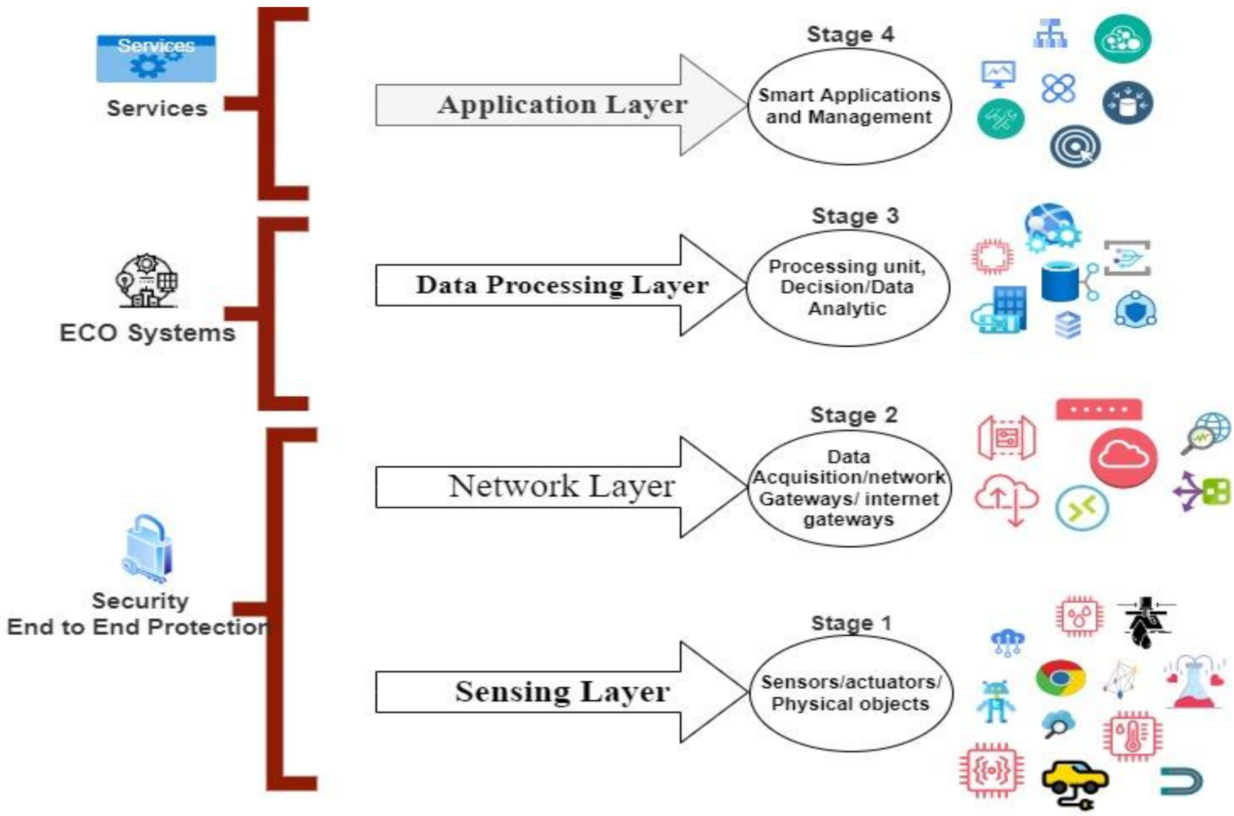

Figure.1.5 IoT Reference Architecture

For the IoT, a seamless connection is a critical necessity. The IoT experience will be impacted by the dependability, speed, and longevity of the network. With the growth of fast mobile networks like 5G and the expansion of regional and urban networking guidelines like Bluetooth, Worldwide Interoperability for Microwave Access (WiMax), and Wireless Fidelity (Wi-Fi), a linked network of things seems possible. Managing the numerous communication protocols that connect these ecosystems, on the other hand, remains complex.

1.4. CHALLENGES IN THE INTERNET OF THINGS

1.4.1. Security

IoT security must ensure that all system components are secure, which is a difficult task for engineers. Since user privacy is in danger, security protocols should progress at the same level as technological advancements. Confidential data must be advantageous for utilizing the IoT's potential rather than becoming a vulnerable component. Technology use and safety improvements go hand in hand alongside market trust. If the IoT acts appropriately with data and delivers on its promises, IoT will reduce the mistrust that emerging technologies may encounter as IoT is first presented to the market.

1.4.2. Costs

To turn technology into a flexible system capable of dealing with current security concerns, engineers must include modifications that result in maintenance fees. Any technology comes with costs, such as employees during the implementation phase, electrical infrastructure, and installation. The cost of IoT development might be an issue.

1.4.3. Connectivity

The connectivity component needs to be addressed for the IoT to keep pace with the modern environment in which people live. This is because connectivity involves more than just information transit; it also entails linking to inherited assets. Though not made for the aforementioned technology, these gadgets can provide crucial information for its intellectual exploitation. By handling time delays, fast transit speeds, and low energy usage, this aims to establish particular criteria.

1.5. APPLICATIONS FOR THE INTERNET OF THINGS

1.5.1 Business

Monitoring oxygen levels and harmful gases in chemical facilities helps assure the safety of both the employees and the products. Keep an eye on the area's temperature. Monitoring ozone levels when drying meat takes place at food facilities. Bus data gathering be done to alert users in real-time in case of crises or to provide them with advice.

1.5.2 Smart Home

IoT connects everyday items to a network utilizing sensors and automation technologies, enabling these objects to carry out tasks and communicate among themselves without requiring human involvement, transforming an automated home into a smart home. This results in a smart home with building automation, networked devices, and IoT. A contemporary smart house can be easily operated with a smartphone, tablet, or computer.

1.5.3 Agriculture

IoT might be utilized in agriculture to improve crop supply and growth by collecting data from environmental sensors. Agricultural product supply and demand have not been adequately controlled despite the fact that the need for farm commodities might be quantifiably expected. This is because diagnosis and pest harm, among other things, could not be predicted due to weather changes and minute differences in harvest circumstances.

To counteract this issue, IoT-based monitoring systems that assess the agricultural environment and a method for boosting the efficacy of decision-making through harvest data are being deployed.

1.5.4 Healthcare

On the other side of the spectrum, IoT is used in smart healthcare to track and assess a patient's physical status; it is much more advantageous for patients who are located far away. IoT healthcare solutions offer remote monitoring of patients suffering from a variety of ailments such as diabetes, Alzheimer's, dementia, and others. These projects will improve access to care while also improving quality and cutting costs.

1.5.5 Smart Transportation

There is less citywide traffic congestion. A detailed view of the city's public transportation system is displayed on a computerized map using city buses' Global Position System (GPS) and estimated time, which also predicts bus arrivals, transit times, and route congestion. According to the information provided, the government may decide to take measures to alleviate the situation to reduce traffic jams and preserve the efficient functioning of municipal buses [22].

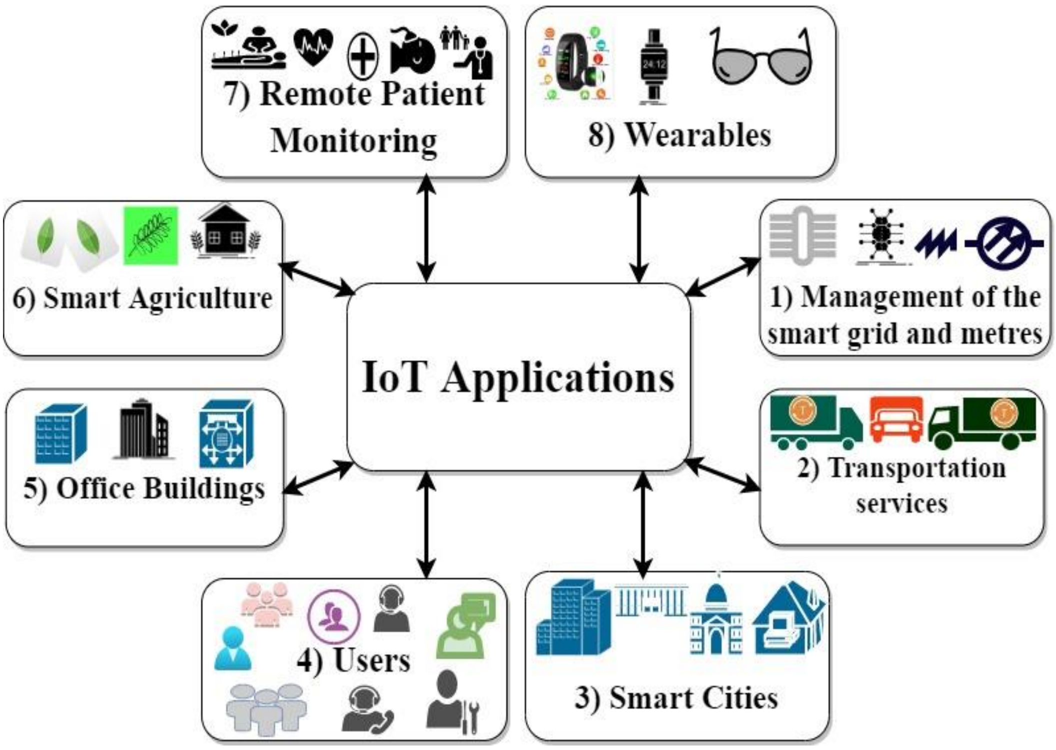

Figure.1.6 IoT Applications

1.6. WIRELESS SENSOR NETWORKS

Military operations were the first to employ wireless sensor networks. Wireless Sensor Networks (WSN) is now being used in a variety of civil projects as sensors become smaller and production prices decrease. The biggest disadvantage is the lack of energy since it is difficult to replace the battery's charge. Several applications need end-to-end dependable data transfer with network congestion to achieve the desired performance, particularly during peak traffic periods.

Smart environments are the next stage in the automation of building, utility, industrial, residential, marine, and transportation systems. The smart environment requires information on both its surroundings and its internal workings. The difficulties in identifying relevant amounts, monitoring and gathering data, analyzing and evaluating information, making good user interfaces, and executing selection and alarm tasks are tremendous. The information needed for smart environments is provided by integrated wireless sensor networks that are in charge of identifying in addition to the initial stages of the computing chain.

Military operations were the first to employ wireless sensor networks. Wireless sensor networks (WSN) are now being used in a variety of civil projects as sensors become smaller and production prices decrease. The biggest disadvantage is the lack of energy since it is impossible to replace or charge the battery. Several applications need end-to-end dependable data transfer with network congestion to achieve the desired performance, particularly during peak traffic periods.

The major goal of something new is to reduce a sensor node's size so that it may be readily distributed throughout a desired region. Contrary to a laptop or Smartphone, each node's are rare that a power supply unit upgraded or charged over its operating lifespan. The most pressing worry in sensors develop today is energy. Sensors are becoming smaller and less expensive as a result of Micro-electromechanical Systems (MEMS) technology. As a result, there have been more civilian uses observed. This section contains details on sensor network applications and components.

1.6.1 Routing

Many judgments must be taken since a decentralized network contains numerous clusters and supports several emails, and because each site is a common resource. There might be several routes from the origin to the end. Message routing is thus a significant subject. The routing method has the greatest impact on performance and packet size latency Quality of Services

(QoS). Routing protocols should also prevent delay and capture. Routing methods include fixed (preplanned), adaptive, centralized, distributed, broadcast, and so on. Perhaps the most fundamental routing system is the token ring. A basic topology and a simple fixed guidelines offer an extremely reliable coefficient and pre-computable Quality of Service (QoS) in this case. A token circles a ring topology indefinitely.

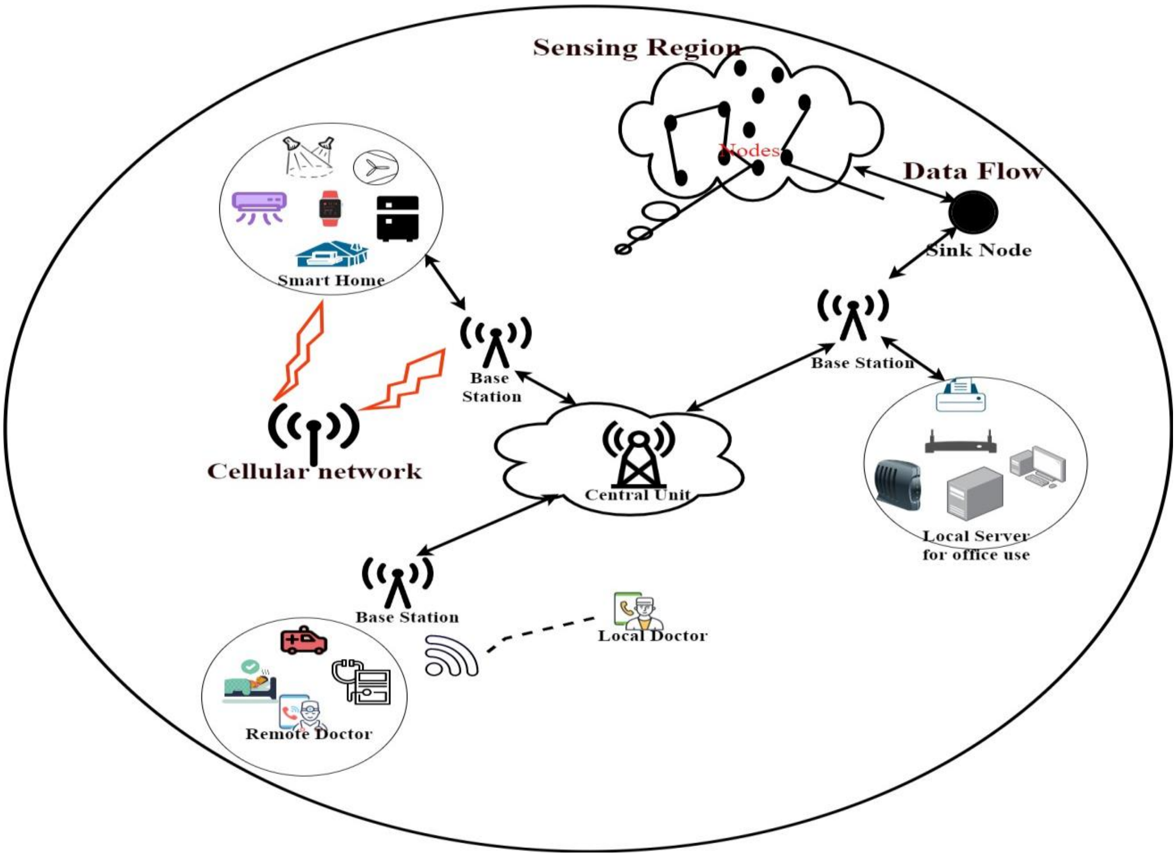

Figure.1.7 Architecture of Wireless Sensor Network

A node gathers the token and includes it in the message when it wishes to transmit one. As the signal travels, the destination inspects the header and seizes the message. In some systems, it adds a "message received" message to the token, which the actual source node then receives. Once liberated, the token can now receive new communications. The ring topology is a truly distributed concept that employs time domain multiple accesses (TDMA) efficiently. Although this system is exceedingly dependable, it wastes network bandwidth. For each message, the token must go around the ring once. As a result, there are several variations of this technique, including the usage of multiple tokens.

Fixed routing techniques frequently employ routing tables, which specify the following node to be directed to base on the most recent message position and the target node. For big networks, database routing systems can be quite huge and cannot account for significant impacts such as nodes with supported queues, or crowded links and broken links. Algorithms for adaptive routing are based on the present network condition and can take into account a variety of performance metrics, such as the price of distribution over a particular connection, congestion on a given link, route dependability, and transmission time.

Shortest path routing techniques determine the quickest route from one node to another. Such approaches can also compute the shortest routes if the price, rather than the distance of the connection, is connected with each connection. For finding the shortest route from a particular node to all other nodes use one of these centralized or decentralized approaches (find the shortest path from all nodes to a given node).

1.7. DIFFERENCE BETWEEN IOT AND WIRELESS SENSOR NETWORKS

- Devices (sensor nodes) are linked without a cable to collect data; Whereas IoT is a physical device (thing) plus a WSN, an IP address, the Internet, an app, cloud computing, etc.
- Wireless Sensor Networks (WSN) gathers and monitors data from physical or natural factors. The Internet of Things, on the other hand, is used to link gadgets and things to the net so that they may interact and share data.
- Wireless sensor networks often consist of a large number of tiny, low-power sensors that wirelessly communicate data to a central base station, while the Internet of Things (IoT) typically consists of lesser multiple devices that are linked to the internet via wired or wireless connections.
- Wireless sensor networks are frequently utilized for monitoring in challenging or hazardous locations. The Internet of Things, on the other hand, is used to link a range of devices and items in more common situations.
- Wireless sensor networks are frequently built to function in certain conditions and for specific purposes. The Internet of Things, on the other hand, is intended to be more generic and adaptable.
- Wireless sensor networks frequently utilize proprietary protocols and technologies, but the Internet of Things depends on standard protocols such as TCP/IP.
- A single organization generally deploys and operates wireless sensor networks. The Internet of Things, on the other hand, is more decentralized, including a range of organizations and individuals.

- Wireless sensor networks are frequently closed systems, with data gathered and utilized just by the deploying company, but the Internet of Things is more accessible, with data shared and used by a wide range of businesses and individuals.
- Wireless sensor networks are generally static, with sensors planted and remaining in a fixed area, but the Internet of Things is more reactive, with devices and things moving around and connecting to multiple networks.
- Wireless sensor networks are commonly used to gather and monitor data. The Internet of Things, on the other hand, is utilized for many functions such as data collecting, tracking, management, and connectivity.
- The wireless sensor network industry is still in its early stages, although the Internet of Things sector is more established.

1.8. INTEGRATION OF BOTH INTERNET OF THINGS (IOT) AND 5G WIRELESS COMMUNICATIONS

A new era of connectivity has begun with the Internet of Things (IoT) and 5G wireless communications integrated together, offering vast device connectivity, low latency, and speed never before seen. Numerous industries are affected by this synergy; including industry automation, smart cities, healthcare, and more.

1.8.1.Benefits

a) Elevated Bit Rates:

5G offers much higher data rates than its predecessors, which allows Internet of Things devices to communicate faster and more effectively.
For applications like augmented reality and driverless cars that need real-time data processing, this is essential.

b) Little Latency

For Internet of Things applications that require fast reaction times, such industrial automation and remote surgery, 5G networks' low latency is revolutionary.
It improves IoT devices' responsiveness and overall user experience.

c) Abundant Connectivity of Devices:

5G supports a massive number of simultaneous device connections, addressing the scalability issues faced by IoT in earlier generations.

This is essential for situations when there is a dense IoT device deployment, such as smart cities.

d) Slicing a network:

Network slicing, made possible by 5G, enables the development of virtualized, specialized networks for certain IoT applications.

Every slice can be tailored to fulfill the particular needs of various Internet of Things applications.

1.8.2. Problems:

a) Costs of Infrastructure:

Costs associated with the deployment of 5G infrastructure are high. This may prevent widespread adoption, particularly in areas with little resources.

b) Issues with security:

As the number of connected devices increases, so does the attack surface. One major difficulty is ensuring the security and privacy of IoT data transferred over 5G networks.

c) Issues with Interoperability:

The diverse ecosystem of IoT devices may face interoperability challenges, hindering seamless communication. While ongoing, adoption of standards is not ubiquitous.

d) Consumption of Energy:

While 5G aims for energy efficiency, the massive deployment of IoT devices can still pose challenges in terms of energy consumption and sustainability.

1.8.3. Future Points to Remember:

a) Edge Computing Integration:

The combination of 5G and edge computing is crucial for processing data closer to the source, reducing latency and enhancing real-time analytics for IoT applications.

b) Integration of AI and Machine Learning:

Leveraging AI and machine learning algorithms on edge devices powered by 5G can enhance decision-making capabilities and enable more intelligent IoT applications.

c) Regulatory Frameworks:

Developing robust regulatory frameworks is essential to address privacy concerns and ensure ethical and responsible use of IoT and 5G technologies.

d) Global Collaboration:

Given the global nature of IoT and 5G, international collaboration is vital for addressing standards, security, and interoperability challenges.

The integration of IoT with 5G holds immense potential to transform industries and improve our daily lives. While challenges exist, ongoing advancements and collaborative efforts are expected to drive innovation, making IoT in the 5G era a cornerstone of the digital revolution. Continued research, investment, and global cooperation will play pivotal roles in realizing the full potential of this transformative convergence.

1.9. SUMMARY

The introduction of fifth-generation technology is followed by discussions of IoT and wireless sensor network technology. The research thesis is described in this section.

This chapter demonstrates how 5G can address the issues facing IoT right now. It gives a brief summary of the existing and upcoming 5G architectures. The poll conclusively shows how 5G can act as the hub of the IoT ecosystem. IoT and 5G may actually complement one another as wireless technologies advance, creating the right ecosystem to meet the demand for IoT devices now on the market. The evolution of IoT devices will thrive thanks to 5G, which has the power to significantly alter behavior. Global alliances will be crucial as the 5G process develops for enabling cross-industry involvement in developing and constructing the 5G system.

The goal of 5G IoT is to link many gadgets inside single network architecture. Intelligent sectors, smart buildings, smart farming, and remote surgery are among the complex 5G wireless applications driving the Internet of Things (IoT) revolution. A high-speed massive link is expected to enable such a large array of intelligent applications under the same tower of 5G wireless communication. The vision of the Internet of Things is currently being developed. Connecting everything, anything, and anytime is an enticing concept. It is difficult to foresee the IoT's distributed nature and its eventual operational scalability; therefore there will be a great deal of responsibility to overcome the obstacles. Scale issues with IP addressability, security, privacy, information management, and statistics will exist.

1.10 THE CHALLENGES FACED IN ENHANCING THE LIFESPAN OF IOT DEVICES AND IMPROVING COVERAGE INVOLVES SEVERAL CRITICAL ASPECTS:

a) **Limited Power Resources:** Many IoT devices operate on battery power, leading to constraints on energy consumption. Prolonging the lifespan of these devices requires addressing power efficiency challenges.

b) **Network Coverage Issues:** IoT devices may face connectivity issues in areas with poor network coverage, limiting their effectiveness. Expanding coverage to reach remote or densely populated areas is a significant challenge.

c) **Security Concerns:** Ensuring the security of IoT devices is a persistent challenge. Cybersecurity threats can impact the functionality and lifespan of devices, necessitating robust security measures.

d) **Device Maintenance:** Some IoT devices are deployed in remote or inaccessible locations, making maintenance challenging. Predictive maintenance solutions are needed to identify and address issues before they impact device lifespan.

e) **Data Management and Processing:** IoT devices generate vast amounts of data, requiring efficient processing and management. Edge computing solutions can help alleviate the burden on centralized systems and improve data processing at the device level.

f) Prospective technological solutions to address these challenges include:

g) **Low-Power Design:** Developing energy-efficient IoT devices with low-power processors and optimized communication protocols can extend battery life.

h) **5G Technology:** Implementing 5G networks can enhance coverage and provide higher data transfer rates, addressing connectivity issues and improving the overall performance of IoT devices.

i) **Blockchain for Security:** Integrating blockchain technology can enhance the security of IoT devices by providing decentralized and tamper-resistant data storage and communication.

j) **Predictive Analytics:** Utilizing predictive analytics and machine learning algorithms can enable predictive maintenance, identifying potential issues before they lead to device failure.

k) **Edge Computing:** Leveraging edge computing capabilities allows data processing to occur closer to the device, reducing latency and improving overall system efficiency

l) **Robust Authentication Protocols:** Implementing strong authentication and encryption protocols can mitigate security risks and safeguard IoT devices from unauthorized access.

m)**Solar and Energy Harvesting:** Exploring renewable energy sources, such as solar power or energy harvesting, can contribute to sustainable and extended device lifespans.

Addressing these challenges and adopting innovative solutions is essential for unlocking the full potential of IoT devices and ensuring their long-term reliability and effectiveness.

1.11. OUTLINE OF THE THESIS

The many strategies utilized in literature to increase the lifespan of IoT are explained in depth in this thesis report. The thesis is organized into seven chapters that present the current research effort. The following paragraphs provide a synopsis of each chapter.

This dissertation work includes a full description of the evolutionary algorithm, various methods used in the research to extend the lifespan of IoT, and the entire procedure to achieve the intended aim, which is separated into the following remaining chapters.

Chapter 2: This chapter presents an overview of State of Art Related Work like MPGA-IoT-5GN, Energy Efficient Topology Control (EDTC), 5G-enabled internet of, Energy Efficient Computing and Communications Mechanisms on IIoT systems, QOS-Adaptive Approximate Real-Time Computation for Mobility-Aware IoT Lifetime Optimization, A Hybrid Technique Based on a Genetic Algorithm for Fuzzy Multiobjective Problems in 5G, Internet of Things, and Mobile Edge Computing, and finally with the research gaps behind all this algorithms.
The research paper "Genetic Algorithm for Higher Ensured Lifespan of Internet of Things In 5G Network". This was published in Computers and Electrical Engineering (Elsevier), Jan 2023, https://doi.org/10.1016/j.compeleceng.2022.108563.

Chapter 3: This chapter presents an overview of Hybridized Mayflies a Meta Heuristics Optimization Algorithm, the Motivation behind the Work, the Inspiration for the Mayfly Algorithm, the Numerical Expression of the Mayfly Algorithm, and the Direction of Male Mayflies: Female Mayflies movement Mayflies Mating, Flowchart of MA, Improved Mayfly Algorithm, Limits of velocity, Coefficient Gravity, Male and Female Mayfly Movement in multi-objective optimization.
The research paper "A comprehensive study on a meta heuristics optimization algorithms-Hybridized mayfly algorithm". This was published international conference (IEEE),

INSPEC Accession Number: ***21779327*** *Added to IEEE* Xplore*:* ***24 May 2022 10.1109/ICOEI53556.2022.9776774***

Chapter 4: This chapter presents an overview of the second algorithm which is used that is Rat Swarm Optimization Algorithm, Introduction, Inspiration, Algorithm for Optimization and Mathematical Representation, Food Acquisition (Prey), Fighting with Hunt (Prey), and Rat Swarm Optimization Flowchart.

The research paper "Chandra, B.R., Kumar, K. (2023). Rat Swarm Optimizer (RSO): A Novel Swarm Intelligence-Based Optimization Algorithm for Tackling Difficult Optimization Problems. In: SoCPaR 2022. Lecture Notes in Networks and Systems, Online ISBN 978-3-031-27524-1, Print ISBN 978-3-031-27523-4, vol 648. Springer, Cham. 28 March 2023, https://doi.org/10.1007/978-3-031-27524-1_52.

Chapter 5: With the help of the above two chapters a detailed explanation of the basic design algorithm i.e., Parallelly implemented Hybridized Mayfly and Rat Swarm Optimizer algorithm (MOP-Hyb-MFRS-IoT-5GN) using Hadoop is explained with different subtopics like, Mapping-Reduce Process in Parallelly implemented Hybridized Mayfly and Rat Swarm Optimizer algorithm, Multi-Objective Programming-Based Hyb-MFRS Algorithm, Fast Non-Dominated Sorting, Merging Solutions for Total IoT, Preferential Selection of Non-Critical Nodes. The suggested prototype's simulated findings are tested and measured in this chapter to confirm and validate them.

Research paper Chandra, B.R., Kumar, K. (2023). "A Parallelly Implemented Hybrid Multi-Objective Efficient Persuasion of Coverage and Redundancy Programming Model for Internet of Things in 5G Networks using Hadoop". Journal of Machine and Computing, Published On: 05 July 2023, Volume 03, Issue 03, Pages: 264-281, https://doi.org/10.53759/7669/jmc202303024.

Chapter 6: The results reached by this research project are discussed in this chapter, along with potential future research projects that may build on it.

Appendix: It deals with the Proposed algorithm followed by fast non-dominated sorting and multi-objective programming techniques and experimental setup used with mathematical calculations to extend the lifespan of IoT by considering different parametric like computing time, energy efficiency, lifespan, and remaining nodes.

CHAPTER -2

LITERATURE SURVEY

CHAPTER -2
Literature Survey

2.1 Introduction

IoT devices are becoming more prevalent in 5G networks because of their applications. The Internet of Things (IoT) coverage issue will be met by the challenge of huge nodes as 5G networks expand and become more popular.

The Internet of Things (IoT) aspires to link anything for the sharing of information and wise choice as technology advances (such as machine-to-machine, cellular communications, machine learning, and big data analysis). Swarm intelligence (SI) enables SI behavior through collaboration in persons with weak or no intellect. To achieve global optimization and take on challenging nonlinear problems, IoT scalability and variation qualities can be used. With the growth of technologies such as big data analytics, blockchain, machine learning, deep learning, and learning techniques, the Internet of Things (IoT) has quickly gained significance. IoT-based solutions provide a smart and autonomous framework for successful decision-making and job automation to enhance life easier for humans. Meta-heuristic algorithms are self-organizing and decentralized algorithms that enhance team intelligence to solve complicated problems. Meta-heuristic algorithms have recently been widely employed to solve a variety of IoT-related difficulties.

Meta-heuristics are a popular strategy for tackling a variety of complicated real-world situations. These algorithms are genuinely inspired by nature's interesting characteristics. The increasing complexity of optimization-based challenges has motivated academics to investigate efficient problem-solving algorithms that focus on decentralized and self-organized systems [87-88]. The behavior of physical phenomena, biological evolution, and living beings such as fish, birds, ants, and beetles inspire meta-heuristics. These are distinguished by relations among residents and produce intelligent behaviors at different group levels [89]. Various meta-heuristics have been created and effectively used for a variety of purposes. Furthermore, the novel algorithms that have been proposed are still being researched and must be proven to be efficient. A variety of reviews for different applications of meta-heuristic algorithms have been offered. This research gathers the breadth of applications and gives appropriate findings for IoT-based applications.

A survey of the literature research works which apply SI-based methods in IoT-based systems. It is divided into three stages. The goal of the first is to identify algorithms and their applications in various problems and contexts, further classifying them based on theory maturity. In the third phase, identify essential elements of SI that might benefit from replication in IoT-based systems and develop some ideas for further study. Preliminary research has previously been conducted in this regard, in which architecture for integrating and employing SI-based methods in IoT-based platforms is presented.

Due to its high requirements, unique qualities, and broad range of applications in a real-time setting, the Hybridized Mayfly and Rat Swarm Optimizer were selected for parallel implementation for thesis work. In the literature study, several methods have been researched to increase node density, processing speed, and the Internet of Things Lifespan.

2.2 Literature Survey on Existing Work

Almost all researchers have proposed methods for the IoT range issue [33-50], however, one of these methods is offered for IoTs with huge clusters in 5G networks. Many researchers have developed numerous meta-heuristic methods to increase IoT coverage, as shown in Table 1 [34].

2.2.1 Simulated Annealing algorithm

To address the sensor deployment issue with the fewest possible sensor nodes, ***Y. E. Khamlich*** [35] proposed a deployment methodology in 2017. This approach relies on the gradient technique and the Simulated Annealing algorithm. The number of sensors and related locations can be heuristically optimized using the suggested method to meet the required application requirements. The method suggested since it is a metaheuristic, many factors need to be adjusted. The accuracy of the figures utilized in their execution has a big impact on how well the outcomes turn out. The efficiency of the algorithm and the amount of time it takes to execute are trade-offs.

*In **2020 Celestine Iwendi*** focused on reducing the energy usage of sensors in the IoT network, which will lengthen the network lifetime. The best Cluster Head (CH) is picked in the IoT network to reduce energy usage. The Simulated Annealing work uses the Whale Optimization Method (WOA) with Simulated Annealing, a hybrid metaheuristic algorithm (SA). Several performance criteria, including the number of living cells, traffic, heat, average energy, and cost function, have been utilized to pick the best CH in IoT network clusters. Even though IoT has a lot of promise in the modern world, there are still a lot of obstacles. Privacy, power management, routing, hardware compatibility, data communication difficulties, etc. are a few of the concerns that must be resolved to improve the IoT's sturdiness. The problem with energy optimization was selection. To solve this problem, the energy usage of the sensors in IoT-based WSNs is optimized using a hybrid metaheuristic algorithm called WOA-SA.

The Internet of Things (IoT) is expanding quickly and serves as the basis for the creation of smart homes, communities, and health care. Huge volumes of data are generated as more and more devices connect to the Internet, posing a significant challenge for processing data. The issues with traditional cloud computing include significant latency. Edge computing is a development of cloud computing that allows for the reduction of cloud computing typically lengthy processing delays. Strategic planning of end nodes has emerged as a crucial research issue as a result of the constrained computational capabilities of edge servers. Most previous research, however, does not take into account the structural properties of the smaller tasks linked between every set of actuators and sensors to solve the task scheduling issue. ***Juan Fang projects in 2021*** suggested a multilevel edge computing system to lessen processing delay and energy use of the edge-cloud system. The directed digraph is the foundation of the program installed in the system and an application module placement approach utilizing the Simulated Annealing Module Placement (SAP) technique to make maximum use of the edge servers was suggested. Each sensor is tied to a certain set of modules in an application. The SAP algorithm is made to determine the best module location for every sensor and to create a module chain that includes a server and module mapping for each sensor. As a result, the edge servers may communicate tuples via the module chain throughout the network.

Unmanned aerial vehicles (UAVs) are a viable method for collecting data from geographically distributed wireless IoT devices. Because this UAV is battery-powered, it must find the quickest route between its sensors. ***Hassan Daryanavard introduced two optimization techniques in 2019***—the simulated annealing algorithm and the ant colony algorithm—and modeled them in three dimensions to compare how well they function and how quickly they can be applied to sensors of various sizes. According to the results, for benchmarks with less than 50 sensors, Simulated Annealing (SA) optimization can be completed more quickly than an ant colony optimization.

2.2.2 Energy Efficient Node Placement Algorithm (EENPA)

In 2014, Kirankumar Y. Bendigeri [36] suggested an Energy Efficient Node Placement Algorithm (EENPA) effort, which aims to effectively place the sensor node in a simulated region, in which all the clusters are similarly distributed along a circular direction to cover the greatest possible space at equal distance. By distributing the nodes over the whole simulation region, less energy is used by each node overall compared to if they were placed at random. In addition to enhancing the network lifespan, this method of determining network lifetime also seems to be more effective than randomly placing nodes.

IoT technology's main objective is to increase resource usage. The IoT network is energy restricted since the network edge (detectors, RFID, controllers, bio-chip, etc.) is battery-operated and connected via low-power channels like IEEE 802.15.4, IEEE 802.11, etc. For energy-constrained IoT Networks, the main difficulty is designing energy-efficient network architecture. Based on the network lifespan, it is claimed that the network is energy efficient. To extend the lifespan of IoT networks, ***P. Sarwesh in 2017***, described how two distinct strategies, such as node positioning and routing, may be effectively combined into a unified network design. In the node placement approach, hierarchical node placement is used to solve unequal data flow. The routing approach uses residual energy-based route calculation to solve unequal energy use. Network complexity is significantly reduced by dividing the energy-related characteristics across two distinct strategies (node placement and routing). According to the results, a good mix of routing and node placement techniques increases network lifetime and improves consistent energy usage.

Sensing and communication-enabled MTC (Machine-type communication) devices may keep an eye on their immediate surroundings and send the data they gather back to the base station (BS) for additional data processing. A clustering structure is required to preprocess the duplicate data due to the large placement of smart sensors to prevent traffic overload. Furthermore, the cost of energy remains a major problem in such IoT systems because of the restricted battery capacity. In a clustered routing technique with low energy consumption, ***Zijing Wang 2018*** suggested an uneven cluster creation technique for network management and energy efficiency in light of the non-uniform traffic distribution. To balance energy usage within each cluster, a decentralized cluster head (CH) rotation method was proposed. To overcome the energy gap problem for long-distance transmitting to BS, a dynamic multi-hop routing method among cluster head (CH) nodes based on a suggested distance- and energy-aware cost function. The output of the suggested method is comparable in terms of network longevity, throughput, and energy efficiency, according to simulation findings.

In the future (5G and beyond 5G) networks, wireless ad-hoc IoT (WAIoT) holds promise for connecting a sizable number of devices. The majority of network nodes in Wireless Ad-hoc IoT (WAIoT) networks are unstable because of the insufficient power supply (such as a battery). To increase the network lifetime, ***PeizhiYan 2020*** concentrated on managing the cluster remaining energy and node degree. To evaluate the network topology, an energy-efficient topology control technique is developed first (called ED-index) (named EDTC). The suggested ED-index technique is used by the EDTC algorithm to reintroduce certain edges into the topology after creating a strong backbone topology using the maximum spanning tree approach. A graph convolutional network (GCN) based method is also being used in parallel to learn how to mimic the original EDTC technique. The suggested EDTC method produces two times the network longevity than the state-of-the-art in the unpredictable communication experiment. Additionally, the GCN-based EDTC method reduces optimization time by almost 99%.

2.2.3 Artificial Bee Colony Algorithm (ABC)

Dynamic deployment of mobile sensor networks using an artificial bee colony algorithm [37] was developed by ***Celal OZT URK in 2021*** to improve functionality by attempting to expand the network's transmission range. The algorithm's successful implementation demonstrates that it may be used for the dynamic development of wireless sensor networks.

An enhanced artificial bee colony method was put out by ***Yinggao Yue, Li Cao, and Zhongqiang Luo in 2019*** to increase the connection and coverage of wireless sensor networks. Obtaining the same coverage and accessibility required time-consuming aspects of WSNs, according to analytical proofs and simulation experiments that compare the random distribution of clusters, genetic algorithms with the proposed algorithm, the number of nodes connectivity rate and perceived relationship, the number of nodes in the network lifetime and perceived relationship, and covering connectivity efficiency.

The Internet of Things (IoT) needs situationally data transfer methods for wireless connectivity. The main obstacle to data transmission through IoT is creating an energy-efficient clustering mechanism. The limited lifespan of IoT, uneven load distribution and significant transmission latency are challenges for the current techniques. ***In 2020, Shamim Yousefi*** suggests a unique cluster-head selection and grouping technique for the Internet of Things. There are two basic aspects to it. Using the Artificial Bee Colony (ABC) method, the first phase chooses the nearly ideal cluster heads. The devices' remaining energy, the number of neighbors, the Distance measured between each gadget and its neighbors, and the Distance measured between each gadget and the sink are all performance criteria. The main goal of the second phase is to organize devices into a few clusters based on the volume of data produced by clusters as well as the Distance measured between each cluster head and its members. Simulation findings show that the proposed method approach reduces transmission latency, longevity, and energy usage.

2.2.4 Redesigned 3D Coverage Model and a Lifespan Framework

A redesigned 3D coverage model and a lifespan framework [38] with guaranteed success are introduced by ***Bin Cao in 2017*** to make it easier to analyze the deployment problem mathematically. Two-particle swarm optimizers, cooperative co-evolutionary particle swarm optimization 2, and the comprehensive learning particle swarm optimizer (CLPSO) are used to solve the NP-hard installation issue. By partitioning the 3D installation area, dispersed parallel predicated on a message-passing interface (MPI) is used to speed up processing.

A well-liked bio-inspired technique called particle swarm optimization (PSO) is used to tackle a variety of optimization issues in fields including artificial intelligence, data mining, robotics, and computer networks. A PSO-based solution was put up by ***Md. Azharuddin and Prasanta K. Jana in 2016*** to address the hot spot issue brought on by multi-hop communications in a cluster-based wireless sensor network. The routing and clustering techniques used in the method have been proven to be energy-efficient. While the traffic burden on the cluster heads (CHs) is uniformly spread during the routing phase, during the clustering phase, the CHs' energy is quickly depleted due to the assignment of a smaller number of sensor nodes. Additionally, a distributed strategy to stop the CHs from dying quickly as a result of total energy depletion is proposed.

Due to its applicability in several disciplinary domains including target recognition, target tracking, and surveillance, 3D wireless sensor networks (3D-WSN) have garnered considerable interest in recent years. The optimization of sensor energy, which establishes sensor architecture to increase network lifespan and energy consumption, is a significant issue in 3D WSNs. The current approaches, such as low energy adaptive clustering hierarchy, centralized LEACH, K-Means, single hop grouping, energy efficient protocol, hybrid-LEACH, and fuzzy C-means, group the networks into clusters where non-cluster head nodes primarily perform sensing function and pass the data to the member nodes, while ch node collects data from other nodes and send to the base station (BS). Although these algorithms lower the network's overall energy consumption, they also result in a significant number of network disconnects, which are the number of sensors that are unable to connect to their cluster heads and the number of sensor nodes that are unable to connect to the BS ***Nguyen***

Thi Tam, Dang Thanh Hai, Le Hoang Son & Le Trong Vinh suggest a solution to this problem based on fuzzy clustering and particle swarm optimization. The suggested technique has been experimentally validated on actual 3D datasets, which shows that it is superior to the methods currently in use.

Since sensor nodes next to fixed sink nodes typically have more traffic to transfer during the transmission process, wireless sensor networks with these nodes frequently experience hot spots problems. It has been demonstrated that using a mobile sink is a successful method to improve network performance, including energy efficiency, network lifetime, latency, etc. ***JinWang YiquanCao BinLi Hye-jinKim SungyoungLee*** proposes a mobile sink-based clustering approach based on particle swarm optimization for a wireless sensor network. When using the particle swarm optimization algorithm for routing, this approach performs the virtual clustering technique. The main factors used to choose the cluster head are the residual energy and node positions. The mobile sink's control technique is well-designed to collect data from the cluster head. The suggested routing algorithm outperforms certain other common routing algorithms in terms of energy consumption, network longevity, and transmission delay, according to extensive simulation data.

2.2.5 Harmony Search (HS)-based Deployment Algorithm

To maximize communication range and reduce network costs, ***Osama Moh'd Alia*** introduced a Harmony Search (HS)-based deployment method in 2016[39]. This algorithm can find the ideal number of sensor nodes as well as their ideal placements. The capability of HS is updated to dynamically grow the ideal number and positions of sensor nodes. This may be achieved by using the idea of adjustable length coding to represent a changing number of potential sensor nodes in each solution vector. The main components of a novel objective function that has been proposed to validate the selection of the ideal deployed sensor nodes and their placements are the transmission range ratio, the frequency of sensor nodes, and the average distance between sensor nodes.

Wireless sensor networks with k-coverage work to set up their infrastructure so that each hotspot zone is enclosed by at least k sensors. The main assessment metrics for such networks are longevity and coverage, therefore putting up a strategy that concurrently expands both of them has a lot of appeals. According to ***Shohreh Ebrahimnezhad, Hoda Jalal Kamali, and Mohsen Ebrahimi Moghaddam in 2011,*** there are two types of nodes: movable and static. To deploy sensor nodes, this technique first attempts to balance energy across sensor nodes in a wireless sensor network with k-coverage and connectivity using the

Improved Harmony Search (IHS) algorithm. Additionally, this approach suggests an appropriate location for an IoT gateway (Sink) that collects information from all devices. Second, a few of the high energy-consumption mobile nodes are eventually shifted to the places that are nearest to the low energy-consumption ones to extend the network lifetime. As a result, the network's lifespan is extended while connection and k-coverage are maintained. Experimental findings supported by computer simulations showed that the suggested IHS-based algorithm identified a superior solution to other relevant approaches.

Similar to wireless sensor networks, underwater acoustic sensor networks' (UASNs) effectiveness is primarily constrained by the lifespan of their sensors. The majority of earlier studies on UASNs did not take network dynamics into account, i.e., in actuality, certain sensors may malfunction over time, run out of battery power over time, or get lost owing to abrupt changes in the underwater environment. For the IoT devices and remotely operated underwater automobiles in this network to dynamically select to sleep or work inability to adjust to the environmental change, ***Chun-Cheng Lin, Der-Jiunn Deng, and Shang-Bin Wang*** took into consideration a UASN in the ocean. The issue at hand is how to dynamically select enough live clusters in the UASN at various times to cover the targets that must be detected. The issue has been proven to have a unique static situation that is NP-complete. To address this dynamic issue, this research suggests an enhanced multi-population harmony search method. The suggested technique performs well in simulations in terms of lengthening network lifetime, resilience, and computation time.

How to send information from network nodes to an access point and select the optimum route for this purpose is one of the most crucial problems in wireless sensor networks. The most efficient route may be determined by many criteria, including energy consumption, reaction time, latency, and data transmission accuracy. The hardest difficulty is lengthening the network lifespan. One of the newest search algorithms is harmony, energy-conscious routing techniques used in small-scale sensor networks. To extend the lifetime of wireless sensor networks, ***Khadije Rahimkhani and Fatemeh Forouzesh*** developed the harmony search algorithm as an effective metaheuristic method for routing. To obtain the desired network balance energy consumption and path length control, this study aims to enhance the performance index for renewable energy in the harmony search algorithm. As a result, it is essential to select each node's beginning energy at random from a set of options since the path's energy consumption needs to be minimal to select a path that can take residual energy into account. In other words, a course of action should be selected to achieve equilibrium between the network's energy usage and the required minimal residual energy.

According to the simulation findings, the suggested objective function offers a lifespan that is 26.12% longer than EEHSBR.

2.2.6 Meta-Heuristic Whale Optimization Algorithm (MADA-WOA)

To address the issue of dynamic sensor deployment, ***Recep "ZDA"*** created a new method in 2017 that is based on the existing meta-heuristic Maximum Area Detection Algorithm-Whale Optimization Algorithm (MADA-WOA) [40]. The dynamical installations of mobile nodes, whose the first assignment was done spontaneously, were performed by the devised technique utilizing the Binary Detection Algorithm to tackle the issue with wireless sensor networks' geographical coverage. The performance of the Wireless Sensor Network at coverage rates was evaluated by contrasting this strategy with the Maximum Area Detection Algorithm based on Electromagnetism-Like in the literature. The strategy created for the area coverage problem is more effective, according to simulation findings, and may be recommended in terms of the number of installed sensing devices, and the network's achieved coverage rates.

One of the biggest issues for the topology control of wireless sensor networks (WSNs) is their longevity. WSN topology control is a method for enhancing the node-to-node connections to lessen interference, conserve energy, and increase network longevity. ***Essam Houssein and Mohammed M. Ahmed,*** introduced the Whale Optimization Algorithm (WOA)-based algorithm known as WOTC, which offers a discrete variant of the WOA in which the positions of each whale are calculated and recorded in binary form. The suggested fitness function is created to take into account two key goals: a reduction in the quantity of network nodes and low consumption of energy within these nodes to overcome difficulties with topology management and lengthen the lifespan of the WSN. Based on the number of neighbors and their sources of energy for active nodes, the analysis indicates that the completed configuration obtained by WOTC is superior to the A3 topology. This was accomplished by using a graph search function to make sure that all nodes chosen for the network are included in the better configuration selection.

Clustering, which involves defining the particle system according to variable values, is the dominant approach used in WSN. In WSNs, the sink nodes are in charge of collecting and processing the data gathered from the cluster members. Knowing the locations of a relay node in WSNs is crucial for energy conservation. According to the meta-heuristic approach, the genetic algorithm, particle swarm optimization, differential evolution, whale optimization algorithm, and grey wolf optimization algorithm are currently becoming effective clustering approaches. A whale optimization technique was presented by ***Biswa Mohan Sahoo, Hari Mohan Pandey, and Tarachand Amgoth in 2021,*** for the evaluation of the network's overall life duration. The main goals of the Whale optimization proposed WOA-P approach are to reduce energy consumption and increase the lifespan of the WSNs. To accomplish these aims, the objectives have been designed to use less energy while extending the network lifespan. The exploratory findings show that the intended whale optimization algorithm, (WOA) outperformed three well-known optimization techniques, including differential evolution, GA, particle swarm optimization, and grey wolf optimization over the network, in terms of reducing overall energy consumption.

2.2.7 Firefly Algorithm (FA)

In 2017, Eva Tuba proposed using the firefly algorithm [41], a modern swarm intelligence technique, for the solution of that challenging multiobjective problem and compared the outcomes of that method with those of other strategies from the research after testing it on a set of reference data. When taking into account all quality parameters, including range, power use, and toughness, the suggested technique was superior.

The sensor nodes used in wireless sensor networks (WSNs), which run on battery power, are used to gather environmental data and send it to the base station. The nodes that collect information shorten the lifespan of the network and consume more power while exchanging data. Energy efficiency is a crucial factor to think about while building sensor networks. The clustering approach's main goal is to transmit data in the most energy-efficient way possible while simultaneously increasing the life of the network. For determining the ideal cluster head selection in the LEACH-C algorithm, ***B. Pitchaimanickam & G. Murugaboopathi 2019*** present the hybrid technique of the Firefly Algorithm with Particle Swarm Optimization (HFAPSO). The combination of methods improves the firefly's overall searching behaviour using PSO and provides the ideal position for the sensor nodes. We evaluate the performance of the proposed strategy in terms of throughput, residual energy, and the total amount of active nodes. The findings demonstrate an improvement in network longevity, which raises the number of active nodes and lowers energy consumption. The suggested approach outperformed the firefly algorithm with regard to output and remaining energy, it was discovered through comparison.

Energy use and network lifetime have been two of the WSN's biggest challenges during the past few decades. To extend the network lifetime of WSNs, ***Sudhakar Pandey, Pranali Navghare, and Deepika Agrawal 2021*** suggested a Fuzzy Logic and Meta-heuristic

Firefly Algorithm based Routing Scheme (FLMFLA). Three factors are taken into consideration by the cluster header while making its selection: the node's remaining energy, its separation from the core of the grid, as well as the cost of connection with the sink node when utilizing fuzzy rules. Following the selection of the cluster header, the cluster header gathered information from the member nodes. The cluster header must choose a node, though, that will use the least amount of energy to transport the data to the sink node, which will be utilized for the optimal swarm meta-heuristic firefly optimization. According to experimental findings, FLMFLA (Firefly Algorithm based Routing Scheme to Increase Lifespan Of the network) improves the quantity of data received by the sink in addition to lengthening the lifetime of the network, throughput, and end-to-end latency.

2.3. RESEARCH GAPS

2.3.1. Simulated Annealing algorithm

In this section, it has been observed from the literature survey that the precision of the numbers used in their implementation has a significant influence on how good the results turn out. If the annealing sequence is lengthy, it may require a long time to operate. This algorithm has lots of adjustable parameters. Because it is a metaheuristic, several factors must be adjusted. The efficiency with which the numbers are implemented has a considerable impact on the accuracy of the output. There is a compromise between the algorithm's output quality and its execution time.

2.3.2. Energy Efficient Node Placement Algorithm (EENPA)

According to the literature review, battery maintenance and energy prices for non-rechargeable clusters are significant and usually hard in hostile conditions. However, because energy-constrained sensor nodes carry out their functions for extended periods, establishing an energy-efficient WSN is challenging. Battery replacement and energy costs for non-rechargeable nodes are high and frequently challenging in hostile environments. The most significant impediments to implementing energy-efficient technology were delay, danger, access to capital, and a lack of knowledge. The most obvious disadvantage of energy-efficient architecture is an environmental concern. Although it is ecologically warm and creates fewer greenhouse gas emissions, it has certain negative consequences on human health.

2.3.3. Artificial Bee Colony Algorithm

According to the assessment of the literature, Artificial Bee Colony Algorithm (ABC) struggles with inadequate utilization while addressing difficult subjects. Secondary information is not being used. However, Artificial Bee Colony Algorithm (ABC) struggles with poor usage while tackling challenging issues. New fitness evaluations on the new evolutionary algorithms are needed. There are more objective function evaluations performed. It is slow to use sequential processing..

2.3.4. Particle swarm optimization

According to a review of the literature, the particle swarm optimization (PSO) technique has the drawbacks of being given to local optimums in greater space and having a poor convergent rate during repeated processes. The particle swarm optimization (PSO) technique has the drawbacks of being given to local optimums in greater space and having a poor convergent rate during repeated processes. The deployment problem and the optimizers are thoroughly understood as a result of extensive experiments employing various numbers of sensor networks and transceivers.

2.3.5. Harmony Search (HS) algorithm

A survey of the literature revealed that The weakness of the Highly Reliable Harmony Search (HRHS) method is in the last iterations where the Pitch Adjustment Rule (PAR) value is close to zero which may cause the method's convergent efficiency to The weakness of the Highly Reliable Harmony Search (HRHS) method is in the last iterations where the Pitch Adjustment Rule (PAR) value is close to zero which may cause the method convergent efficiency to stagnate.

2.3.6. Whale Optimization Algorithm

According to a survey of the literature, the basic problem with WOA, like other meta-heuristic algorithms, is the algorithm's slow convergence rate. The existing Whale Optimization Algorithm (WOA) has significant shortcomings, including delayed convergence, low solution accuracy, and a propensity to slip into the local optimal solution.

2.3.7. Firefly Algorithm

According to a review of the literature, Firefly Algorithm has several shortcomings; including long computation times, slow convergence, and others. Yang suggested the Firefly algorithm (FA) as a swarm intelligence method in 2008. The typical FA has various drawbacks, such as computational complexity computation time, and poor convergence speed.

2.4 SYNOPSES OF THE FEATURES OF THE RAT SWARM AND MAYFLY ALGORITHMS:

Two examples of nature-inspired optimisation algorithms are the Mayfly Algorithm and the Rat Swarm Algorithm, which are based on the ways in which mayflies and rats behave. It's crucial to remember that, despite the special qualities and benefits of these algorithms, the existing approaches do not inherently fall short of their expectations. Rather, these algorithms that draw inspiration from nature are presented as different ways to tackle optimisation issues. Below is a quick synopsis of the features of the Rat Swarm and Mayfly algorithms:

Algorithm Mayfly:

Inspiration: Mayflies' short life span and unique reproduction mechanism served as the model for the Mayfly Algorithm. Mayflies must locate mates and procreate swiftly throughout their short adult lives.

Features: During the algorithms brief adult life, objective functions are optimised by imitating the swarming behaviour of mayflies. Its main objective is to quickly explore and utilise the search space.

Benefits: The Mayfly Algorithm is appropriate for some optimisation issues since it seeks to accomplish quick convergence and effective solution space search.

Rat Swarm Methodology:

Rats' cooperative foraging behaviour serves as the model for the Rat Swarm Algorithm. Rats collaborate to maximise their search strategy and locate food.

Features: To address optimisation issues, this method simulates the swarm intelligence of rats. To effectively navigate the solution space, cooperation, communication, and adaptive techniques are required.

Benefits: The Rat Swarm Algorithm can handle dynamic, multi-modal, and complicated optimisation issues. It makes use of the swarm's collective intelligence.

Although these algorithms offer advantages, they are not designed to fix a flaw in the way things are done now. For a variety of issues, conventional optimisation techniques and heuristics like simulated annealing, particle swarm optimisation, and genetic algorithms are still useful. The type of optimisation problem, its properties, and the particular needs of the application all influence the choice of algorithm to be used.

In order to investigate various facets of optimisation, improve performance in particular situations, or address issues that can profit from distinctive swarm intelligence behaviours, researchers frequently provide novel methods. To fully grasp these algorithms' advantages and disadvantages in various problem domains, it is imperative to conduct an empirical assessment of these algorithms and juxtapose them with current approaches.

2.5 Conclusion

The literature review highlighted network lifetime issues that needed to be resolved to optimize energy usage for the network. Numerous meta-heuristic methods were developed to increase IoT coverage. Power control has an impact on energy consumption performance measures. Power management is necessary to extend the network lifespan.

Battery life necessitates energy-efficient transmission techniques as well as effective IOT coverage. In this work, the coverage difficulty of IoTs with multiple nodes is divided into several smaller problems, which are then tackled simultaneously using Hadoop. Finally, parallel operation successfully tackles the IoT coverage problem through big nodes by purposely expanding the IoT's lifespan. The simulation study is based on node performance characteristics such as computation time, longevity, and energy efficiency.

According to a survey of the literature, the suggested technique has the potential to dramatically improve the energy efficiency, coverage area node redundancy, and lifetime of Internet of things devices.

CHAPTER -3

A HYBRIDISED MAYFLY ALGORITHM

CHAPTER -3

A HYBRIDISED MAYFLY ALGORITHM

3.1 Introduction

Many optimization techniques were put out as solutions by various researchers. Even still, some algorithms still struggle to solve problems, making it difficult for researchers to identify those that are more effective. Similar to both the most and least value, optimization is the procedure for figuring out the best result for the function. One of the most recent suggestions was for the Mayfly algorithm [53]. This mayfly algorithm can distinguish between male and female mayflies based on their distinct update behaviors. The Mayfly optimization states that if the current position is distant from the best candidate, the person will move to the best position at a low speed, in contrast to this, if the current position is close to the best candidate, the individual will run more quickly. The convergence rate will be sluggish in such a scenario. As a result, the equation is rebuilt for the single and enhanced Mayfly method. This chapter discusses the mayfly algorithm method which these algorithms are unique in that they will find the optimal solution in the first iteration. The Mayfly Algorithm offers a suitable alternative for both multiobjective and discrete problems, and its application can be used in a variety of fields as well as other industrial and engineering optimization problems. Different optimization tactics were suggested to deal with the problems outlined above. Finding more effective algorithms is a challenging undertaking for researchers as certain algorithms continue to be unable to tackle issues. The process of figuring out the function's ideal response is referred to as optimization, much like figuring out its highest and lowest values. The Mayfly algorithm was subsequently recently suggested [53].

Although the Mayfly Algorithm may be implemented in any computer language, Matlab was chosen because of how simple it is to use structure arrays and create visualizations of data. On 6^{th} gen Intel core, 1 TB hard drive with 8GB of RAM, all simulations were run. Additionally, the performance of each algorithm version was assessed by contrasting it for a certain number of function evaluations.

3.1.1 Motivation

Let's briefly review the Ephemeroptera insect species, often known as Mayflies, before learning about the Mayfly algorithm. Ephemeroptera is one side of a historical group of insect species known as Palaeoptera. They were given the name "Mayflies" because, in the

United Kingdom, they only appear in the season of May [54]. With the aid of several reference papers, it was determined that the Mayfly optimization technique is the industry standard after completing 25 test functions and categorizing them into 3 groups, including multimodal, unimodal, and fixed dimensions [55]. The results show that the Mayfly approach outperforms common Metaheuristics algorithms in terms of both local and global search capabilities. Even though Mayfly is occasionally one of the speedier methods, it has a good possibility of discovering the global optimum. The Mayfly findings for discrete problems and multi-objective optimization are adequate [56].

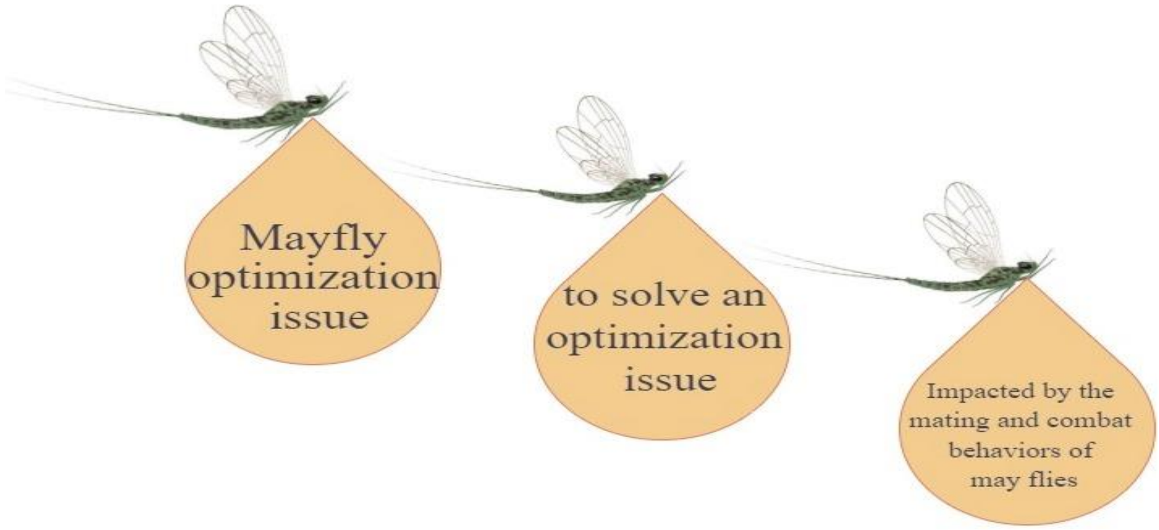

Figure.3.1 Mayfly Optimization Algorithm

3.2 The development of the Mayfly algorithm

Even though we can see adult mayflies with our unaided eyes and they spend a long time developing as aquatic nymphs before becoming adults and prepared to climb to the surface, their behavior includes flocking up, evolution, crossover, and wandering after hatching from the eggs and copulating [57]. The mature mayfly only lives two to three days before reproducing. Adult male mayflies begin monial dance on the water's surface in groups by making up and down motions to attract the female mayflies. After a brief period of mating, the female flies fly into the groups of male flies, finish their union, and then dump their eggs into the water's surface, continuing their life cycle [58]. The last two are the benefits of the recommended method that promote exploration. Additionally, by applying various equations separately for males and females, exploration may be improved in this study. The mayfly spends its entire year as a nymph in freshwater doing nothing. The mayflies fly off to locate a partner later that year, deposit some eggs, and then immediately perish [59].

3.2.1 Mayfly Algorithm Mathematical Interpretation

Tsafarakis and Zervoudakis [60] created the Mayfly algorithm, which solves the most recent method optimization issue. It is one of the hybrid optimization strategies that combine the benefits of modern optimization methods like genetic programming [61] and particle swarm optimization [62]. The male and female populations of mayflies are first created at random from two varieties of mayflies. Or, to put it another way, each mayfly is randomly positioned as a single solution in the issue space, as shown by a vector dimensional.

$$D = (D_1, D2, \ldots\ldots\ldots, D_{dim}) \quad (1)$$

Each mayfly's location and direction of movement change as they fly, allowing for active social and individual communication. This active communication is known as velocity (V), and it is represented as

$$V = (V_1, V_2 \ldots V_{dim}) \quad (2)$$

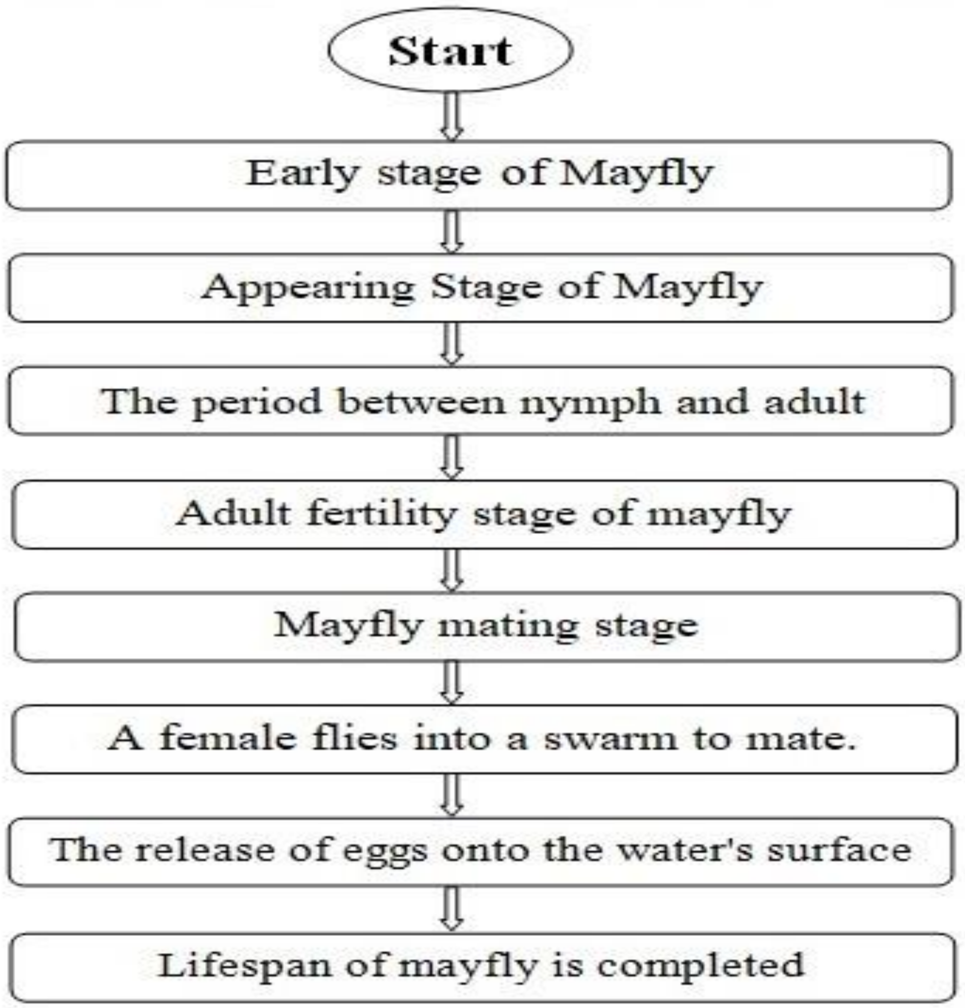

Figure.3.2. Flowchart of mayfly lifecycle

3.2.2 Male Mayfly Direction:

Males grouping together indicates that each mayfly's location is altered based on its neighbors and their experiences, and the Mayfly algorithm's components are as follows:

$$D_x^{T+1} = Dx^T + V_x^{T+1} \quad (3)$$

$$D_x^0 \sim (D_{min}, D_{max}) \quad (4)$$

Dx^{T+1} is the new position created by adding the current position Dx^T and velocities Vx^{T+1}, where Dx^T is the mayfly's current location and 'x' is the space seeking at time T+1. As male flies move quickly above the water's surface. The following phrase may be used to determine the mayfly's speed:

$$D_{xy}^{T+1} = D_{xy}^{T+1} + \Omega_1 S^{-\alpha R2m} (P_{bestxy} - Z^T_{xy}) + \Omega_2 S^{-\alpha R2m} (Q_{bestxy} - Z^T_{xy}) \quad (5)$$

D_{xy}^{T+1} is the mayfly's speed in vector y at the current time,

The identical mayfly's location at time y is represented by Z^T_{xy}, and its continual attraction, represented by y, Ω_1, Ω_2 is utilized to compute both the social element and intellectual consequences. The static sight of a mayfly to other objects is a parameter, and the gravitational constant is parameter m. The excellent posture is P_{bestxy}, while the desirable male mayfly position is Q_{bestxy}. Considering the issue of minimizing

$$P_{Best_{xy}} = \begin{cases} D_x^{T+1}, & if\ g(V_x^{T+1}) < g\ P_{best_{xy}} \\ is\ kept\ the\ same, & otherwise \end{cases} \quad (6)$$

where "g" is the target value used to determine the solution's quality.

The final Cartesian distance is C_p, which is the range among Z_x and P_{bestx}, as opposed to C_g, which is the range among Z_x and Q_{bestx}. These may thus be computed as

$$\|Z_k - X_k\| = \sqrt{\sum (Z_{xy} - X_{xy})^2} \quad (7)$$

3.2.3 Female mayflies flying

Female flies, which may be distinguished from male flies, do not congregate in groups; instead, they fly toward male flies to mate.

$$V_x^{T+1} = V_x^T + V_x^{T+1} \quad (8)$$

$$V_x^0 \sim (V_{min}, V_{max}) \quad (9)$$

3.2.4 Breeding Mayflies

With the aid of the mutation operation, the mating of two mayflies is represented: Each parent is chosen from among the population of men and women [63]. The process of choosing parents is comparable to how men are drawn to women. Depending on fitness, or at random, will be chosen. After calculating the crossing of the female and the male using previous data, the two descendants will be produced and expressed as

Descendants 1 = R* Parent male + (1-R)*Female (10)

Descendants 2 = R* Parent Female + (1-R)*Male (11)

Here R is the value that must fall between a certain range of 0 and 1 [64]

3.2.5 Flowchart of MA

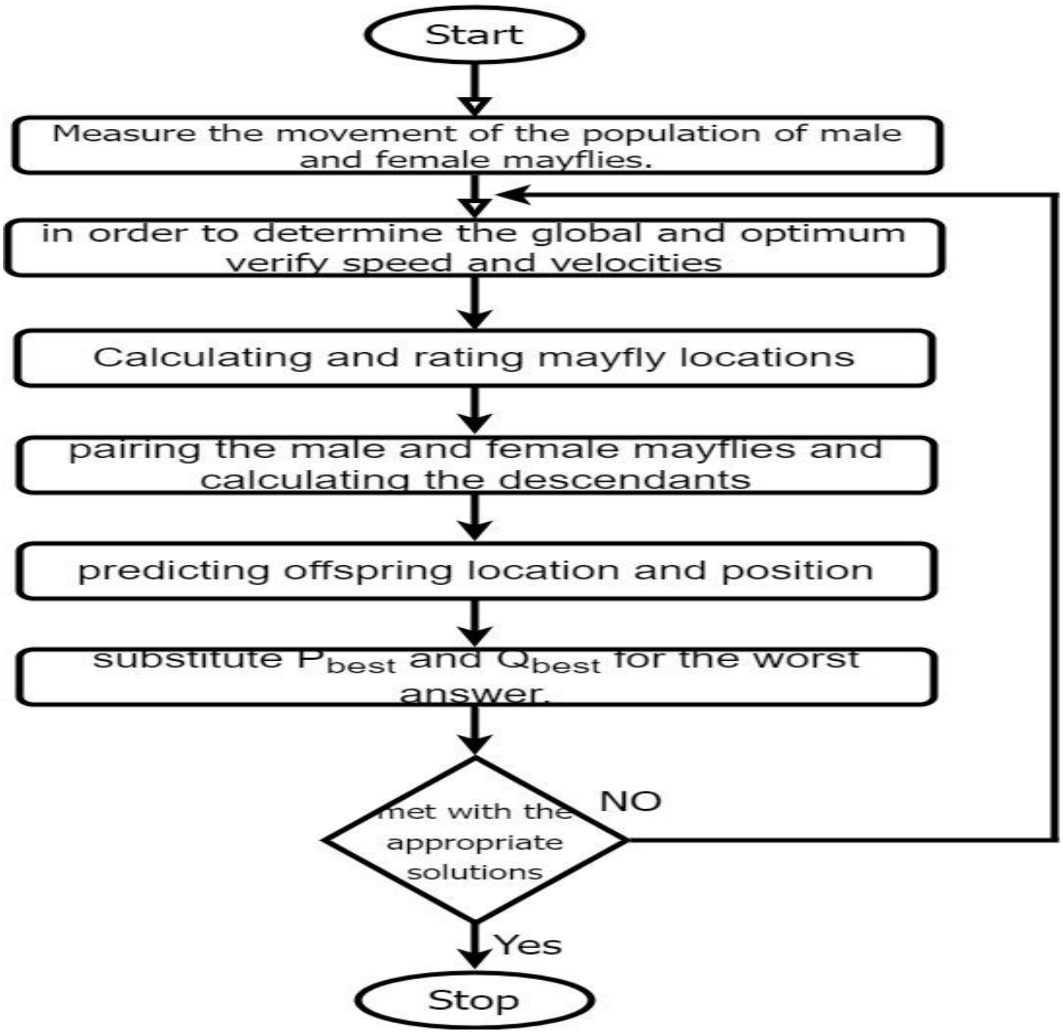

Figure.3.3 Flowchart of mayfly algorithm

3.3 Mayfly algorithm Enhancement

After analyzing the study data using a fundamental method, stability problems caused by the velocity-induced disorder of the current solution were found. Early adherent action was also seen in the algorithm; this is because the exploitation and exploration phases lacked sufficient stability. The method has evolved to include updating, which is explained below, to address these issues.

3.3.1 Constraints of velocity

After monitoring the fundamental algorithm's tested values, it was found that high values cause velocity to explode fast, which causes the mayflies to flee the issue space. This led to the notion that every mayfly was capable of increasing the maximum velocity V_{max}, even though genuine mayflies do not increase their speed on the water's surface. When this occurs, the velocity is altered as

$$V_{xy}^{t+1} = \begin{cases} V_{max}, & if\ V_{xy}^{t+1} > V_{max} \\ -V_{max,} if\ V_{xy}^{t+1} < -V_{max} \end{cases} \tag{12}$$

The interesting thing about this is that when V_{max} regulates the exploration of the search space, even for low values the exploitation can be stopped far from the ideal value. Vmax values can be chosen to be

$$V_{max} = rand*(x_{max} - x_{min}) \tag{13}$$

the range of rand is from 0 to 1.

3.3.2 Density Factor

In this situation, the density factor G, which is employed in the Particle Swarm Optimizer inertia weight, will aid in achieving the balance between exploitation and exploration even with the velocity restriction. The revised equation for determining the density factor G in a set value in the ranges of 0 and 1 is given below.

$$G = G_{max} - \frac{G_{max} - G_{min}}{Iteration_{max}} * Iterartion \tag{14}$$

Where iteration is the current iteration, G_{max} is the number of iterations, G_{min} is the lowest number of iterations, and G_{max} is the maximum value of gravity.

3.4 Multi-objective optimization: Male and Female Mayfly Migration

In multi-objective problems, the male mayfly's motion is identical to that in the single-objective solution. When the Q_{best} leads the male mayfly, equation (5) is utilized; otherwise, equation (13) is used.

Similarly, the following formula is employed for female flies

$$D_{xy}^{T+1} = f(x) = \begin{cases} G * D_{xy}^{T} + \Omega_2\, S^{-\alpha R2m} \left(Q_{best_{xy}} - Z_{xy}^{T} \right), & \text{if male dominates females.} \\ G * D_{xy}^{T} + fl * y, & otherwise \end{cases} \tag{15}$$

Equations (10) and (11) are utilized for the breeding season, in which the male and female are chosen according to their rankings, and crossings are performed using each mayfly's optimal position to advance the convergence behavior of the Mayfly multi-objective algorithm.

3.4.1. Mayfly algorithm compared to better algorithms.

According to research work, Mayfly can determine the preferred value among all test functions while running on the same configuration with various challenges, and Mayfly Algorithm (MA) has demonstrated superior performance than different algorithms in terms of efficiency and precision. Another key characteristic that aids in convergence while providing the benefits of having the solutions in both low and high velocities concurrently is the low intensity of Mayfly and zero rates of Offspring intends to investigate the Mayfly Algorithm's implementation while contrasting the outcomes with those of better metaheuristic algorithms, particularly the particle swarm optimizer, Genetic algorithm, firefly algorithm, differential evolution, Harmony search, and Bees algorithm.

After Conducting Several Test Functions and comparing the results, it can be shown that Mayfly is superior to the other algorithms [8]. 11 unimodal clearly outlining was run, and Mayfly discovered superior values across all dimensions. Finding the global optimum is discovered to be quite challenging, however, the Mayfly algorithm identified higher outcomes on several functions, moving the Particle Swam optimizer to the next stage with five values.

Parameter	**Genetic Algorithm (GA)**	**Particle Swarm Optimization (PSO)**	**Harmony search (HAS)**	**firefly algorithm (FA)**	**differential evolution (DE)**	**Bees Algorithm (BeA)**
Population size	100	60	60	25	50	45
Dimension of Inertia	-	0.8-0.45	-	-	-	-
Rate of cross over	0.95	-	-	-	0.1	-
Rate of Mutation	0.1	-	-	-	0.9	-
Harmony assessment rate	-	-	0.9	-	-	-
Min Bandwidth	-	-	0.0001	-	-	-
Max Bandwidth	-	-	1	-	-	-
Total number of chosen Sites	-	-	-	-	-	3
The number of elite sites	-	-	-	-	-	1
Bees near Elite Points	-	-	-	-	-	7
Bees near Specific Locations	-	-	-	-	-	2

Table 3.1: Values of the specifications utilised in GA, PSO, HAS, FA, DE, and BeA.

From the preceding study, it can be concluded that the recommended Mayfly Algorithm is more effective in terms of efficiency and accuracy when compared to other algorithms. By running with the same setup on all problems, Mayfly discovered excellent values for the majority of test functions. Due to males' nuptial dance, females' random flight, and genetic mutation, Mayfly is capable of escaping while other algorithms are trapped in local optima.

Having both low and high speeds at once is one of the algorithm's benefits, as is the fact that mayflies have a lower speed and their progeny have a zero-speed generation.

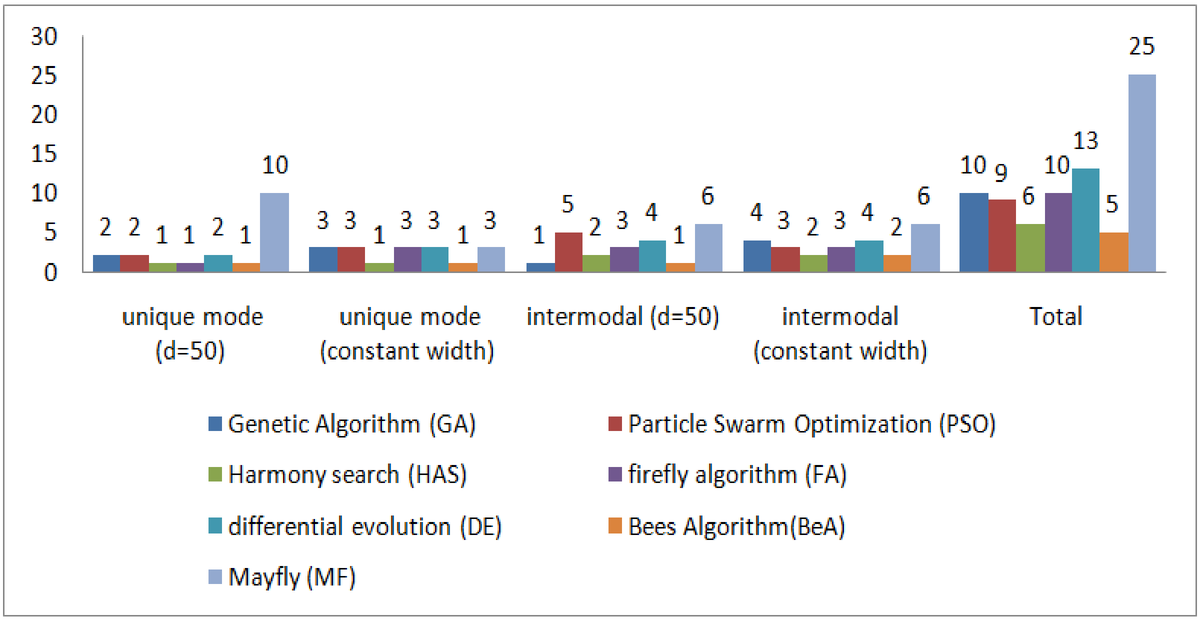

Figure.3.4 shows the algorithms' best results for various functional groups.

3.5 JUSTIFICATIONS FOR THE MAYFLY ALGORITHM'S

The goal of the Mayfly Algorithm is to replicate the swarming behaviour of mayflies, with an emphasis on their quick adult life cycle exploration and exploitation tactics. Although the Mayfly Algorithm's status as a "ideal candidate" is contingent upon the particular criteria of an optimisation problem, it is deemed beneficial in some circumstances. The following are some justifications for the Mayfly Algorithm's perceived promise:

Quick Convergence:

The method is designed to take use of the quick decision-making processes seen in mayflies in order to achieve rapid convergence.

Because mayflies only live a little time, the algorithm must rapidly converge to the best answers in the allotted amount of time.

Effective Investigation:

During the adult life stage, mayflies efficiently explore their surroundings.

This exploration approach is incorporated by the algorithm to efficiently search the solution space and find optimal or nearly optimal solutions.

Flexibility:

Mayflies are renowned for their capacity for adaptation and swift response to changes in their surroundings.

Because the Mayfly Algorithm frequently incorporates adaptation mechanisms, it is appropriate for dynamic optimisation issues in which the best solution may vary over time.

Intelligent Swarms:

The programme utilises swarm intelligence, which is modelled after the collective actions of swarming mayflies.

Swarm intelligence enables the algorithm to take advantage of individual agent cooperation, coordination, and communication, which results in effective problem-solving.

Multi-Modal Efficiency:

It is well known that mayflies have multimodal behaviours, allowing them to adjust to varying environmental circumstances.

The Mayfly Algorithm is intended to tackle multi-modal optimisation issues in which the fitness landscape may include more than one optimal solution or peak.

Heuristics Inspired by Nature:

Algorithms inspired by nature frequently take advantage of biological systems' efficacy and efficiency.

The Mayfly Algorithm uses these heuristics to tackle certain optimisation problems, drawing inspiration from the natural behaviour of mayflies.

It's crucial to remember that the type of optimisation problem at hand determines how effective the Mayfly Algorithm will be. There is no one-size-fits-all approach to optimisation, even though it might work well in some circumstances. In order to comprehend the advantages and disadvantages of the Mayfly Algorithm, researchers usually evaluate its performance and contrast it with alternative optimisation techniques in a variety of problem domains.

3.6 MAYFLY ALGORITHM DIFFICULTIES LIMITATIONS

Like any optimisation algorithm, the Mayfly Algorithm might run into difficulties and be limited in some circumstances. The following scenarios could pose challenges for the Mayfly Algorithm, prompting researchers to investigate other possible solutions:

Complicated Fitness Environments:

The Mayfly Algorithm may have trouble navigating through optimisation problems with extremely rough and complex fitness landscapes, where the objective function has a lot of local optima.

Elevated Dimensional Areas:

When dealing with high-dimensional optimisation problems, the effectiveness of the Mayfly Algorithm may decline. The curse of dimensionality may affect the algorithm's search performance as dimensionality rises.

Tough Trade-Off between Exploration and Exploitation:

Although the Mayfly Algorithm seeks to balance exploration and exploitation, it may occasionally find it difficult to adjust quickly enough to environmental changes, which could result in less-than-ideal performance.

Changing and Noisy Scenes:

Conditions that are noisy fitness evaluations or frequent, erratic changes can be problematic. The flexibility of the Mayfly Algorithm might not be enough to efficiently handle noisy fitness landscapes or fast dynamics.

Agents' Limited Communication:

The Mayfly Algorithm depends on agent communication and swarm intelligence. In situations when communication is expensive or restricted, the algorithm might not be able to take advantage of group decision-making.

Large-Scale Adjustment:

In complex optimisation problems with a large number of variables and a huge solution space, the Mayfly Algorithm may not be able to find optimal solutions quickly enough.

Speed of Convergence in Basic Landscapes:

The Mayfly Algorithm may converge quickly and overshoot ideal solutions in fitness landscapes that are smooth and reasonably basic. In situations where a faster convergence is not advantageous, this could be considered inefficient.

Insufficient Variety in Solutions

Because the Mayfly Algorithm relies on swarm intelligence, it may not find as many diverse solutions as it could. This could happen, for example, if the swarm converges too soon to a suboptimal location, which would restrict the algorithm's capacity to find high-quality, diverse answers.

Scholars frequently take these variables into account and carry out empirical investigations to assess the benefits and drawbacks of the Mayfly Algorithm in a range of issue domains. If the algorithm is less successful in a certain situation, this encourages researchers to investigate different optimisation strategies that might be more suitable for resolving the problems at hand.

3.7. HYBRIDIZED MAYFLY ALGORITHM SPECIFICALLY RELATES TO THE RESEARCH OBJECTIVES:

With particular research goals in mind, the Hybridised Mayfly Algorithm was created with the intention of addressing major issues in the context of Internet of Things networks. Let's examine the connections between this method and the aforementioned study goals:

3.7.1. Increasing Life Expectancy:

The goal of the hybridised Mayfly algorithm is to maximise resource usage in the Internet of Things. The method helps extend the life of IoT devices by effectively controlling their energy consumption.

The algorithm's adaptive techniques minimise pointless processes and improve communication, which lessens total device wear and tear.

3.7.2 Cut Down on Redundancy:

In Internet of Things networks, redundancy can result in inefficient use of resources and higher energy usage. Using optimisation approaches, the Hybridised Mayfly Algorithm finds and removes redundant data in processing and transmission.

The algorithm guarantees the reduction of duplicate jobs through intelligent decision-making processes, hence enhancing the streamlined and effective functioning of the Internet of Things network.

3.7.3 Expanding the Reach:

In Internet of Things networks, coverage is crucial, particularly when a large region needs to be watched over. The processes of the Hybridised Mayfly Algorithm allow for the strategic deployment and management of sensor nodes in order to improve coverage.

The algorithm helps to maximise the coverage area while making sure that vital zones are sufficiently monitored by optimising node placement and adjusting to the dynamic nature of the environment.

3.7.4 Efficiency of Energy:

Given that devices' power supplies are frequently limited, energy efficiency is a major challenge in Internet of Things networks. Energy-conscious decision-making is incorporated into the Hybridised Mayfly Algorithm.

The algorithm has the ability to employ adaptive mechanisms to dynamically modify the energy consumption patterns of devices. This allows for the efficient allocation of energy and the reduction of wasteful energy expenditure.

3.7.5 Overall Integration: The Mayfly algorithm, which is renowned for its versatility, is strengthened by the Hybridised Mayfly Algorithm, which combines it with extra optimisation methods. It makes dynamic adjustments to the ever-changing IoT environment to guarantee optimal network performance and achievement of predetermined goals.

3.7.6 Technical Approach: The programme combines optimisation techniques, environmental change adaptability, and swarm intelligence concepts to accomplish these goals. By dynamically balancing the trade-offs between redundancy, energy consumption, and coverage, it offers an all-encompassing answer to the problems that IoT networks face.

3.7.7 Future Considerations: The Hybridised Mayfly Algorithm may require additional improvements, integration with cutting-edge technology, and validation in a variety of Internet of Things scenarios as it continues to be researched and developed. It is a viable option for meeting the changing requirements of IoT networks, adding to their longevity, efficacy, and efficiency because of its optimisation and flexibility qualities.

3.8 Conclusion

The fundamental Mayfly Algorithm has been covered in this chapter. These algorithms integrate crossover, grouping, mutations, nuptial dance, and random walk with the benefits of current algorithms that are inspired by how adult mayflies behave. The other key benefits of the recommended method are those that promote exploration. Furthermore, it was shown by this study that employing separate equations for males and females in each group increased the exploration.

By studying the data and analyzing the findings, in conclusion in terms of both global and local searching abilities, the Mayfly algorithm beats the most popular metaheuristic optimisation methods. The suggested approach will arrive at the best result in the earliest iteration, leading to the unusualness of these algorithms. The Mayfly Algorithm produces sufficient solutions for situations that are both multiobjective and discrete.

CHAPTER -4

ALGORITHM FOR RAT SWARM OPTIMIZATION

CHAPTER -4

ALGORITHM FOR RAT SWARM OPTIMIZATION

4.1 Introduction

In the year 2006–21 spans, significant optimizers have been developed for the creation of swarm metaheuristic approaches inspired by the animal kingdom. The study is organized taking into account the living things through the repeat action mechanism. The combined data revealed that around 38 percent of the total of the algorithm, which is dependent on animal behavior, is inspired by spineless creatures and approximately 62% by vertebral species. The Rat Swarm Optimization method, which is a biography-influenced algorithm, is used in this work to resolve optimization problems. One of the driving forces behind this algorithm optimizer is the behavior of the rats in the surroundings. This study discusses the mathematical formulations of these activities, as well as certain real-world restricted engineering, described problems. To stop the recommended approach from being used, mathematical exploration, exploitation testing, and combining exploration was done. The recommended Rat Swarm approach is amazing in addressing the actuality concerns when outcomes are observed and compared to all other better optimization techniques.

A problem-free structure is provided, a powerful Metaheuristics algorithm that will offer instructions and a flowchart for creating analytical optimizing compilers [66]. At the moment, the algorithm for the debts is built up based on the rules and uses the common structure [66]. Recent years have seen an increase in recommended Metaheuristics algorithms for improvement as well as their progress, searching techniques, and hybridizations, according to a survey [67]. The mathematical formulations for improved algorithms were preserved in IEEE for reference and research reasons [68] in many conferences and journal articles. Hussain [67] offered a comprehensive taxonomy of analysis that included the fundamentals, updates, and applications by focusing on all metaheuristics. The narrative agenda of the collection of evocative techniques are described in [69].

Those approaches this escalates have been tasked with seeking better solutions for pressing problems when concert methods fail to deliver the desired product within the allotted time and supplies employed. The NFL (No Free Lunch) [70] theorem is used for all new optimizers for constructing the newest algorithms, updating, and methods, as there is no doubt that the analysts will never be satisfied with the present Metaheuristics [71]. According to the progression technique, genetic algorithms make up the earlier metaheuristics algorithm from the 1960s to 1970s; nevertheless, in pursuit of a suitable metaheuristic optimization, analysts concentrated on a new beginning point of motivation. Today's metaheuristics are vast, with numerous theories derived from the behavior of microscopic creatures, bacteria, and viruses. This essay seeks to identify the key route through which the analyst might explain the important optimizers' production process in terms of inspiration.

The environment-creatures acted as the model for the creation of algorithms to address the many optimization problems [72]. In actuality, these kinds of algorithms are employed to determine the optimal result based on the "cut and try" methodology. Due to their simple theoretical structure and little requirement for grade data, these algorithms are also quite simple to implement [73]. These optimizer algorithms were mostly inspired by the choice of natural and social behavior of biological forms. As a result, the Rat Swarm Optimizer algorithm examines the chasing and killing actions of rats in the vicinity. Merging and statistical surveys are also looked into to validate the Rat Swam Optimizer algorithm's exploration and exploitation in addition to the avoidance of local optima [74].

4.2 Inspiration

Based on structural findings, rats are semi-mammals with lengthy tails [75]. Different species of rats include brown and black ones. Male and female rodents are referred to as "bucks" and "dos," respectively, in the rat family. A high degree of environmental intelligence is displayed by these rats. They participate in a variety of activities and exchange information [76]. Rats are a type of local animal in which the males and females remain in the same group. Rats frequently engage in extremely aggressive behavior that may cause the demise of some creatures [77]. This aggressive conduct when hunting and murdering for sustenance served as the primary source of inspiration for this piece. To create the rat swarm optimizer algorithm and perform optimization, the mathematical expression for the hunt and kill behaviors of rats was modeled in this study.

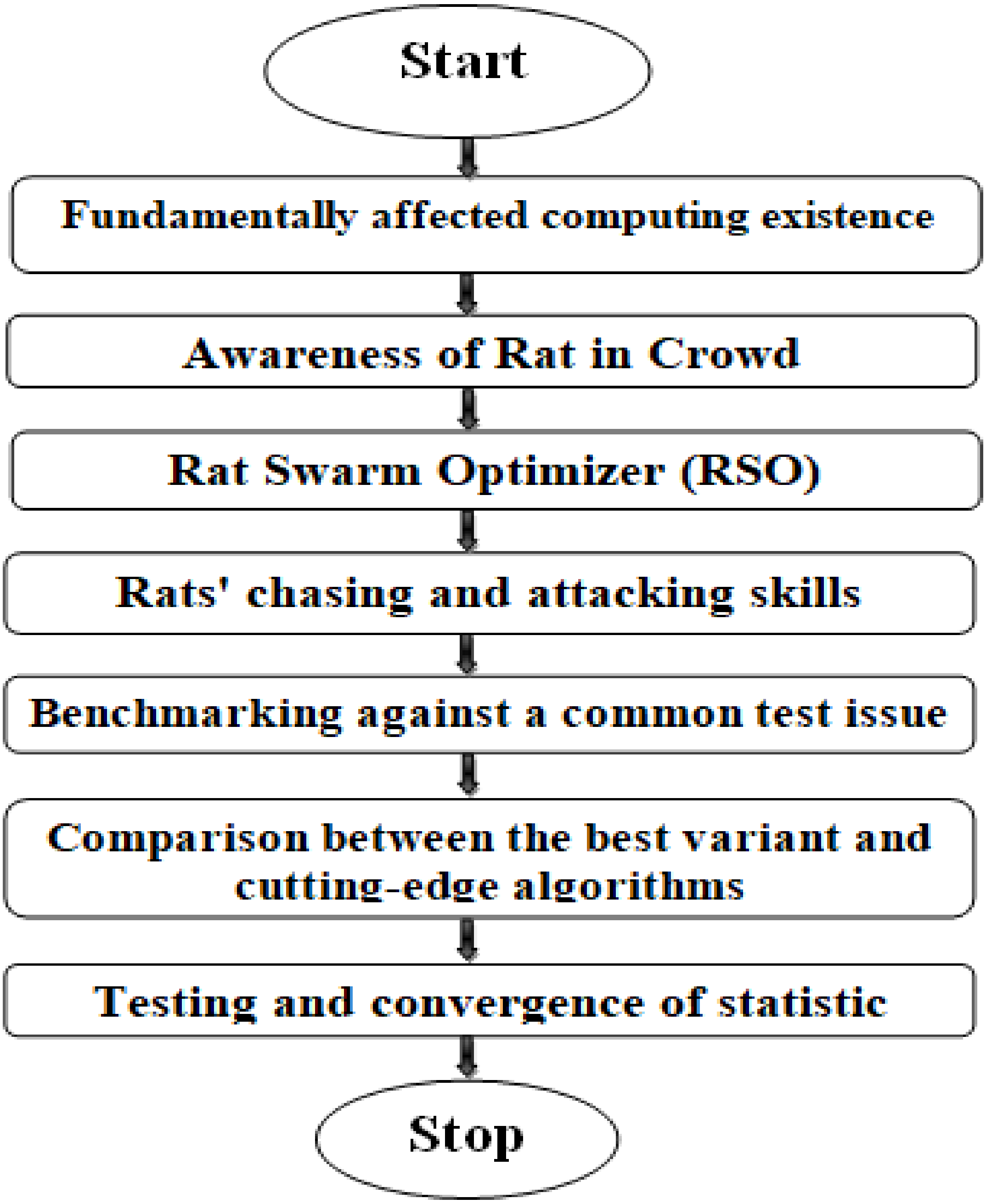

Figure 4.1 Overview of Rat Swarm Optimizer Algorithm

4.3. Algorithm for Optimization and Mathematical Representation

The attack and chasing actions of rats are described in the sections that follow. After that, a summary of the recommended Rat Swarm Optimizer algorithm follows.

4.3.1 Food Acquisition (Prey)

Rats are typically aggressive, self-seeking creatures that chase their victims in swarms. With the assumption of a better search agent who was skilled at locating the prey to mathematically depict the behavior of rats. In light of successful search agents thus far, other agents can modify their placements.

The equations suggested in this process are listed below:

$$\overline{P} = X \cdot \overline{P_a}(U) + Y[\overline{P_b}(U) - \overline{P}_a(U)] \quad (1)$$

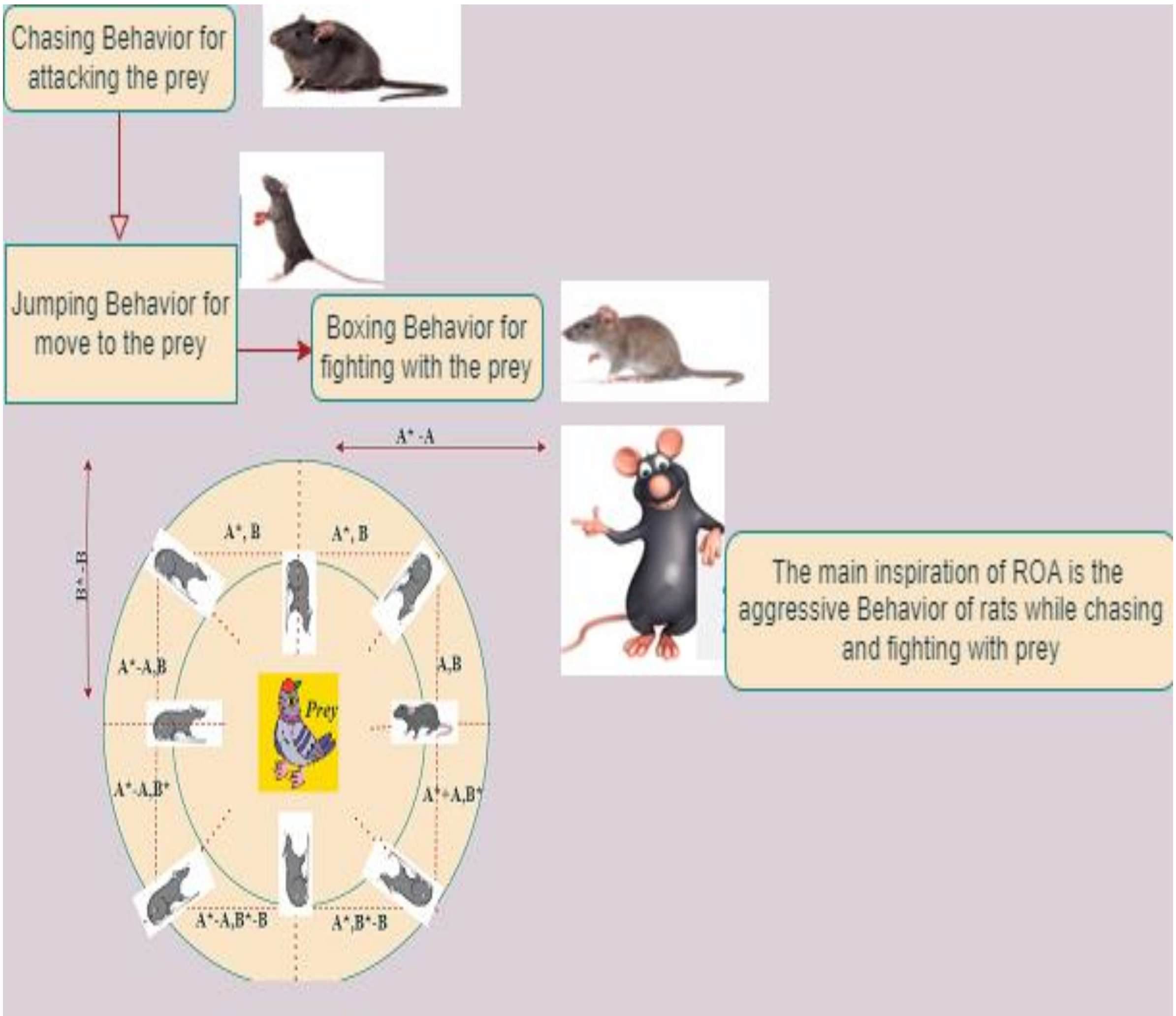

Figure 4.2 Rat Swarm Optimizer's model-building source

The parameter $\overline{P_a}(U)$ identifies the rat's location, and the ideal solution $\overline{P_b}(U)$ is specified by/in either case, the following equation is used to compute the parameters X and Y:

$$X = P - Rand \cdot \left(\frac{P}{(Max_{iteration})}\right) \quad (2)$$

$$Rand = 0, 1, 2, 3 \ldots Max_{Iteration} \quad (3)$$

$$Y = \text{Hunting the prey} = 2 \cdot Rand\,(\,) \quad (4)$$

As a result, the ranges of different numbers [78] P and *Rand* are [1-5] and [0-2], respectively. The parameters for effective exploration and development of X and P are behind, over the flowing cycles.

4.3.2 Fighting with Hunt (Prey)

The following equation defines the differential formula for the actions of rats hunting for prey:

$$\overline{P}_a(U+1) = \overline{P_b(U) - \overline{P}} \qquad (5)$$

The rat's subsequent revised location is $\overline{P}_a(U+1)$. The placement of other search agents is adjusted to the best answer, which is stored [79].

The effects of formulas (1) and (5) are illustrated in a three-dimensional (3D) setting in Figure 4. Figure 4 provides a good explanation of how rats update their location from (A, B) to the prey position. Several of the options indicated in the previous equation (2) can be used to replace the current position (4). In any event, this idea may be expanded thanks to n-dimensional domine. Therefore, exploitation and exploration may be assured by altering the levels of factors A and B. The proposed Rat Swarm Optimizer method retains the desired outcome with fewer operators.

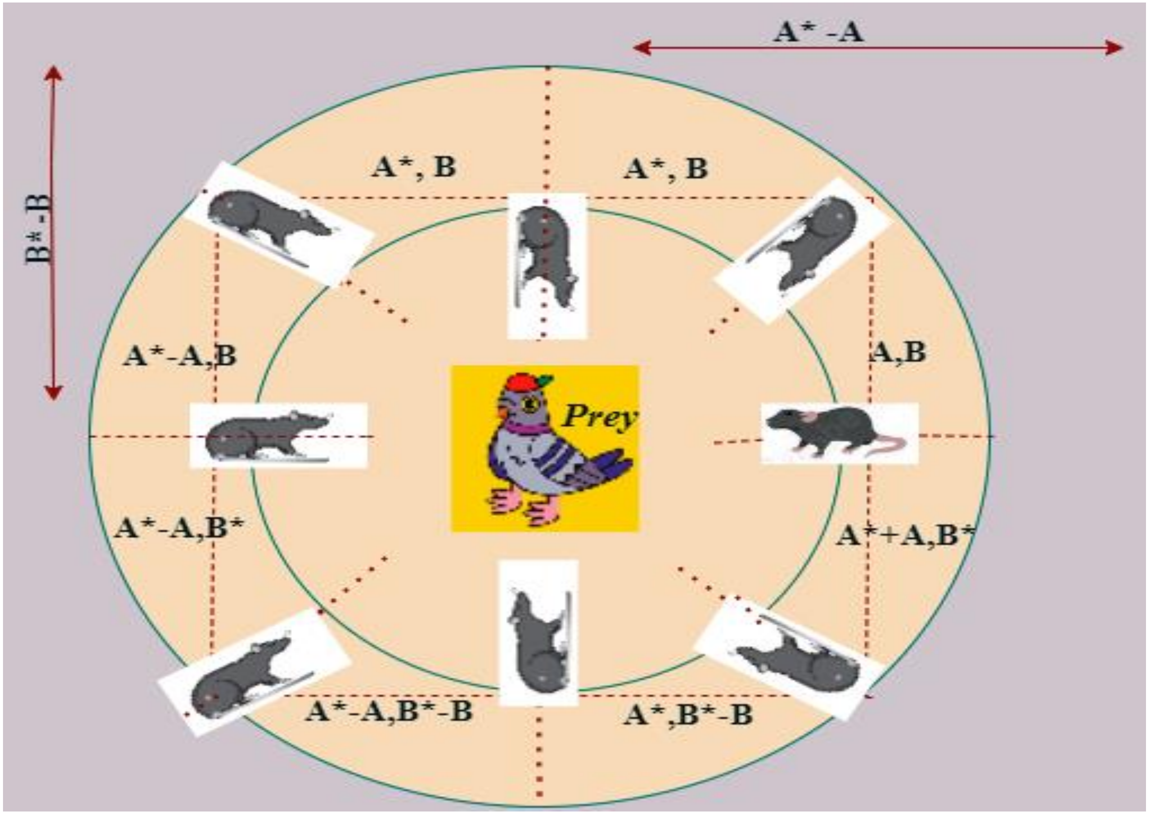

Figure 4.3 Rats' 3D vector positions

4.3.3 Rat Swarm Optimization Flowchart

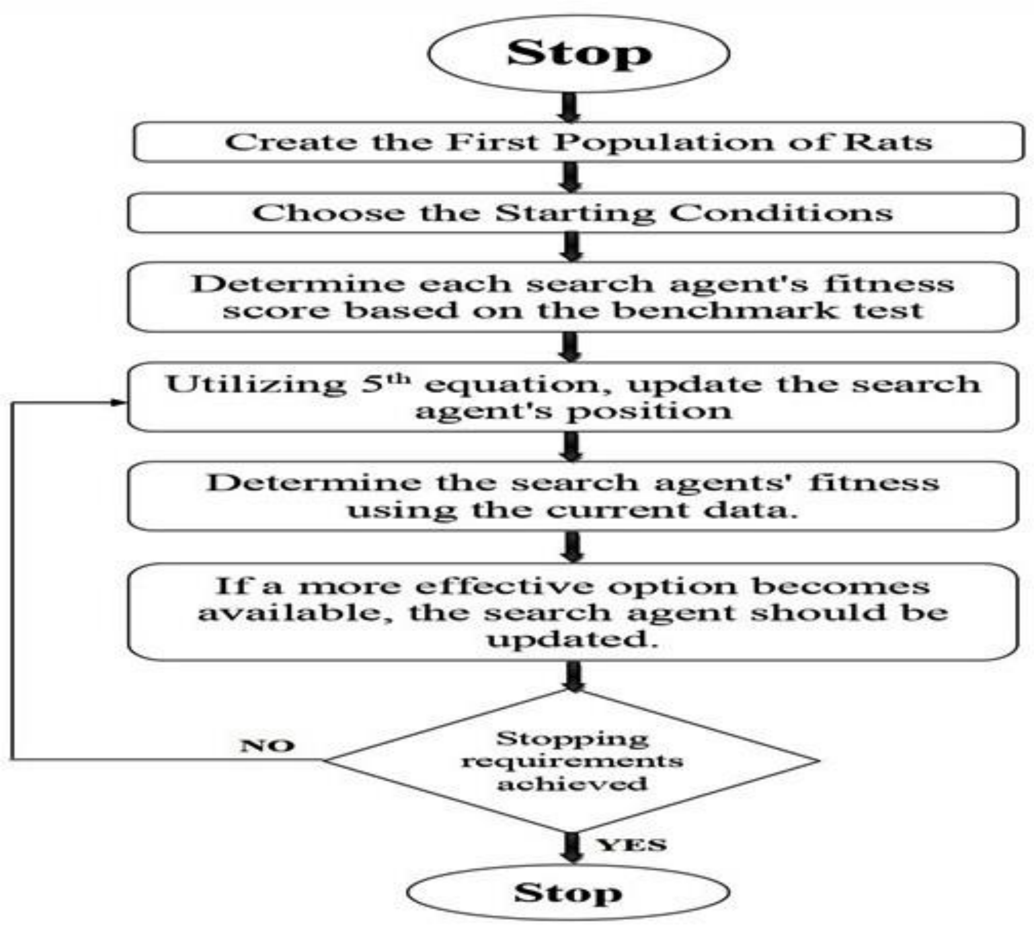

Figure 4.4 ROA flowchart

The flowchart for Rat Swarm Optimization is shown in the phases above.

Rat population initialization in

Stage 1 for i=1, 2, 3, and so forth.

Stage 2: Choosing the X, P, and Y parameters for the Rat Swarm Optimizer.

Stage 3: calculating the fitness value of each search representative

Stage 4: In the accessible space, research is done to get the best search representation.

Stage 5: places the search representative equation in a new position in

Stage 6: Verify that each search representative is well beyond the space search's bounds and make any required adjustments.

Stage 7: Measure the updated value, check for representative fitness, and modify the vector Pr.

If there is any success, go back to the original ideal solution.

Stage 8: If the condition is satisfied, end the algorithm. In any other case, repeat step 5.

Stage 9: Restore the successful solution that was acquired.

4.4 Problems with Computing

4.4.1Time constraint

1. It takes *O (i * d)* time to alter the answer to an evaluation procedure. within the boundary of the quantity of Rat Swarm Optimization population, where ‘i’ specifies the quantity of repetitions and ‘d’ describes the ratios.

2. Then to determine each search representative's fitness, an $O\ (Max_{iteration} * i * d)$ period is required, where $Max_{iteration}$ is the maximum number of iterations required to recreate the recommended Rat Swarm Optimization process.

3. Stages 1 and 2 would be performed till the required result is found (T).

As a result, the Rat Swarm Optimization algorithm's ultimate time complication is $O\ (Max_{iteration}\ .\ i\ .\ d\ .\ T)$.

4.4.2 Complications with space

The total space used during the initialization phase using the Rat Swarm Optimization method. The Rat Swarm Optimization algorithm's space problem is defined as the maximum quantity of space to be consumed previously examined during its formatting procedure. As a result, the Rat Swarm Optimization algorithm's space complication is *O (i*d)*.

4.5. Designing Engineering Problems Using Rat Swarm Optimization

In this part, two engineering formulation issues with realistic constraints are examined using Rat Swarm Optimization techniques. The issues are as follows: speed reducer design issue [91], pressure vessel issue [90],

4.5.1 Pressure vessel design plan

The pictorial representation viewpoint of a pressure vessel is presented in the following Fig. 6, which is ideal at both ends by meridian heads, so order to reduce the overall cost of materials. The four design variables are (v1-v4):

(v_1, width of the shell) W_s.

(v_2, width of the head) W_H.

(v_3, inner diameter) I_D.

(v_4, length of the cylinder portion) C_L.

Where I_D and C_L are W_s, W_H, are continuous design variables, and each one has an integer-based value that is more than or equal to 0.0625 in.

Note $\acute{\upsilon} = [v_1\ v_2\ v_3\ v_4] = [I_D, C_L, W_s, W_H]$, Minimize f (ύ) = $0.6224v_1v_3v_4 + 1.7781v_2v^2{}_3 + 3.1661v^2{}_1v_4 + 19.84v^2{}_1v_3$,

Disposed to

g1 (ύ) = $-v_1 + 0.0193v_3 \leq 0$,

g2 (ύ) = $-v_3 + 0.00954v_3 \leq 0$, (5)

g3 (ύ) = $-\prod v2_3v_4 - 4/3 \prod y^3{}_3 + 1, 296, 000 \leq 0$,

g4 (ύ) = $v_4 - 240 \leq 0$,

Variable scale

$0 \leq v_1 \leq 99$,

$0 \leq v_2 \leq 99$,

$0 \leq v_3 \leq 200$,

$0 \leq v_4 \leq 200$,

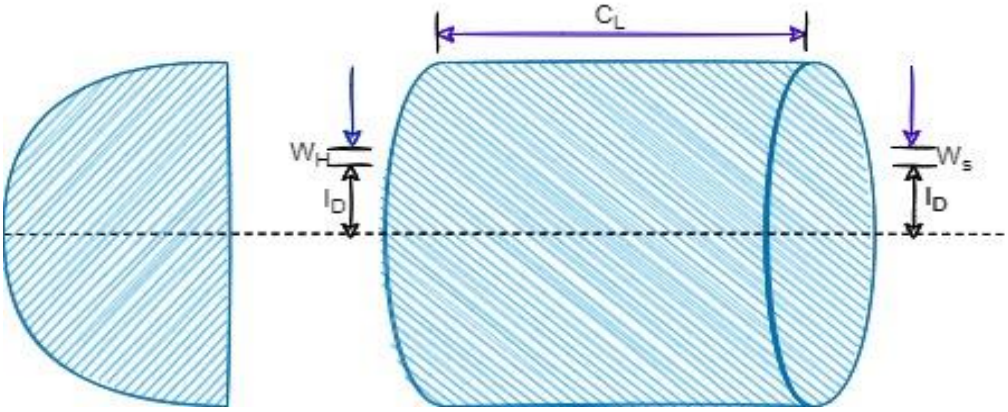

Figure 4.5 Pressure Vessel Problems in a Schematic View

Algorithms	Optimum variables				Optimum cost
	ST	HT	IR	CL	
SHO	0.76	0.36	40.21	200.00	5870.51
GWO	0.76	0.36	40.3	199.6	5889.33
PSO	0.76	0.36	40.3	200	5891.3
MVO	0.83	0.39	42.01	157.2	6011.71
RSO	0.78	0.36	40.27	200	5876.72
SCA	0.8	0.4	41.21	182.7	6127.21
GA	0.73	0.39	41.45	199	5893.21
HS	1.02	0.89	44.43	180	6553.2

Table 4.1 pressure vessel design problems results of different algorithm

Rat Swarm Optimization, when compared to the other algorithms displayed in Table 2 above yields the best results in terms of the best solution and optimal design with the lowest cost.

The analytical findings regarding the pressure vessel design error are, however, illustrated in the graphic that goes along with it. As can be observed, the Rat Swam optimizer method performs better in comparison to other more sophisticated algorithms. Figure 7 shows how these design challenges are merged, demonstrating that the suggested technique can merge exceptionally precisely during the early rounds.

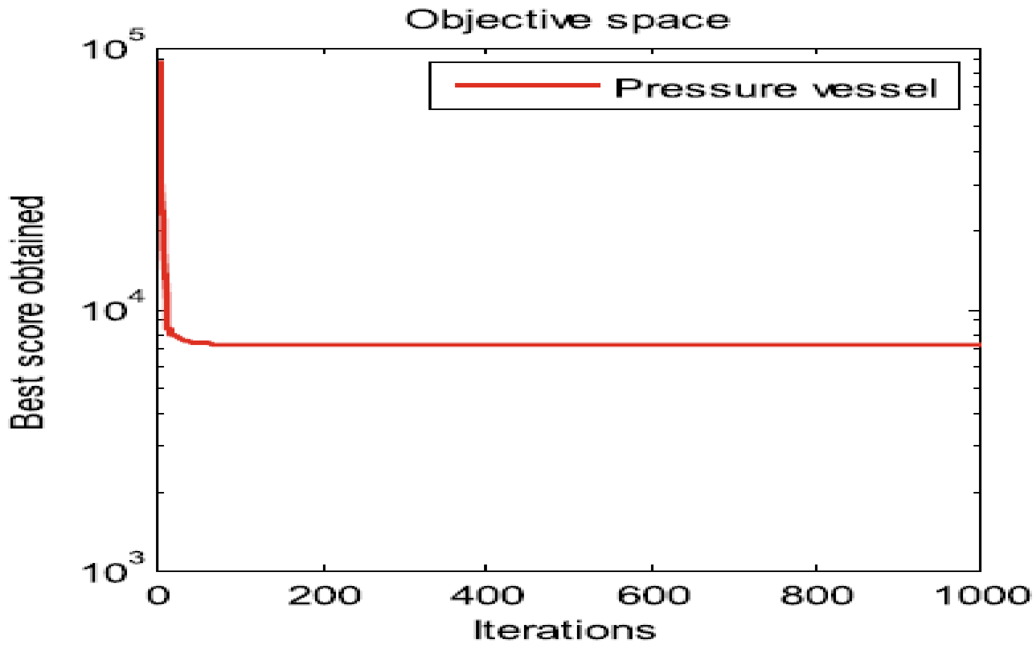

Figure 4.6 an examination of several Rat Swarm Optimization suggestions for the pressure vessel problem

Algorithms	Best	Mean	Worst	Standard Deviation	Median
SHO	5886.2	5888.5	5890.2	166.0	5882.0
GWO	5890.3	5892.0	5894.2	13.2	5891.3
PSO	5891.0	6532.2	7393.9	533.1	6415.9
MVO	6012.1	6476.9	7251.1	328.0	6397.6
RSO	5879.1	5882.0	5887.2	167.9	5881.1
SCA	6136.9	6325.9	6512.2	127.1	6319.1
GA	5891.1	6265.0	7005.9	497.0	6113.0
HS	6552.0	6644.9	8005.9	657.6	7587.1

Table 4.2 RSO's analytical performance in contrast to other algorithms for the pressure vessel design issue

4.5.2 Pattern problems when lowering speed

The construction of a reduced range, which contains seven designing variables, is one of the most challenging challenges. This is a minimization problem of the optimization problem that is depicted in Fig. 8 and is intended to reduce the pressure of the torque converter.

1. The gear teeth's bowing pressure is one of the design's constraints.
2. External Influence.
3. The beams' diagonal turns.
4. The tension in the beams.

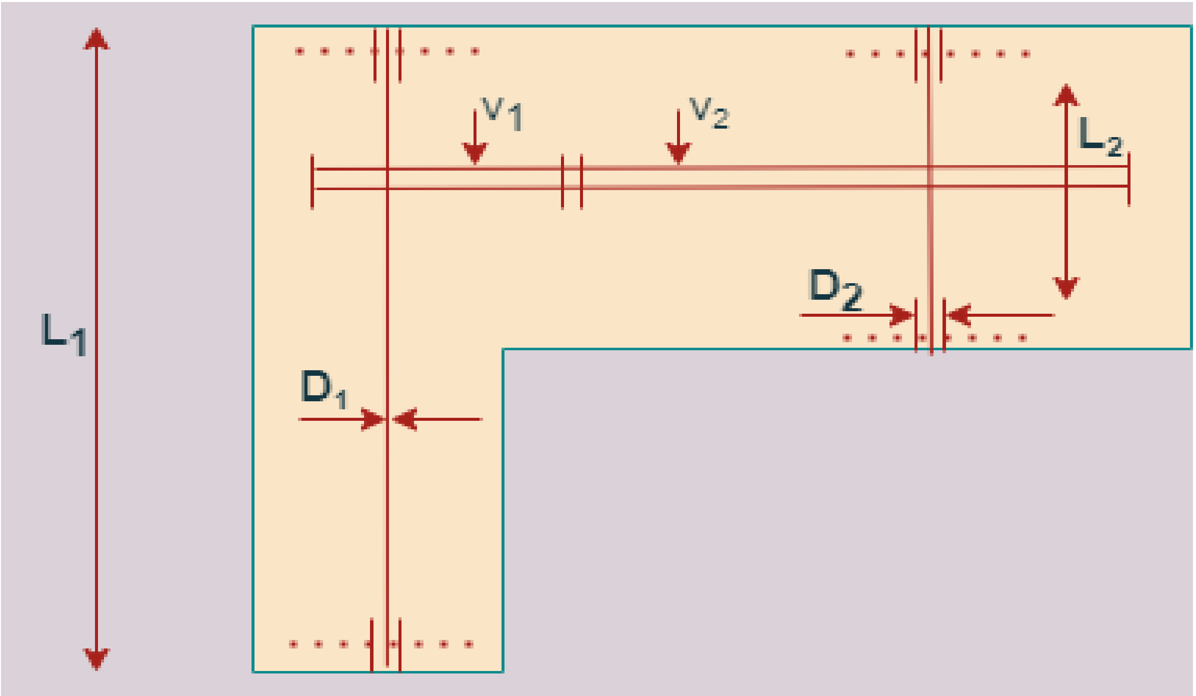

Figure 4.7 Schematic depiction of the speed reducer problem

There are seven input parameters *(v1–v7)*. The first shaft's diameter *(D1)*, second shaft's diameter *(L2)*, first shaft's length among bearings (L1), and pinion's number of teeth *(P)* are the parameters *(D2)*.

The mathematical formula of this problem is as follows:

Decrease f (y) = 0.7854v1v22 (3.3333v23 + 14.9334v3 − 43.0934) − 1.508v1 (v26 + v27) + 7.4777(v36 + v37) + 0.7854(v4 v26 + v5 v27),

Subject to

g1 (ύ) =27/v1v22v3 − 1 ≤ 0,

g2 (ύ) =397.5/v1v22v23 − 1 ≤ 0,

g3 (ύ) =1.93v34/v2v46v3 − 1 ≤ 0,

$g4\ (ύ) = 1.93v35/v2v47v3 - 1 \leq 0,$

$g5\ (ύ) = [(745(v4/v2v3))\ 2 + 16.9 \times 106]1/2/110v36 - 1 \leq 0,$

$g6\ (ύ) = [(745(v5/v2v3))\ 2 + 157.5 \times 106]1/2/85v37 - 1 \leq 0,$

$g7\ (ύ) = v2v3/40 - 1 \leq 0,$

$g8\ (ύ) = 5v2/v1 - 1 \leq 0,$

$g9\ (ύ) = v1/12v2 - 1 \leq 0,$

$g10\ (ύ) = 1.5v6 + 1.9/v4 - 1 \leq 0,$

$g11\ (ύ) = 1.1v7 + 1.9/v5 - 1 \leq 0,$

Where, $2.6 \leq v1 \leq 3.6$, $0.7 \leq v2 \leq 0.8$, $17 \leq v3 \leq 28$, $7.3 \leq v4 \leq 8.3$, $7.3 \leq v5 \leq 8.3$, $2.9 \leq v6 \leq 3.9$, $5.0 \leq v7 \leq 5.5$

Different optimization techniques were evaluated, and the statistical results and better-produced optimum results were described [92]. The rat Swarm Optimization technique is the effective optimizer for the speed reduction design problem, according to an analysis of the results using superior algorithms. Figure 4.8 demonstrates that, when compared to more advanced strategies, the Rat Swarm Optimizer algorithm achieves the best results and delivers effective merging action across several generations.

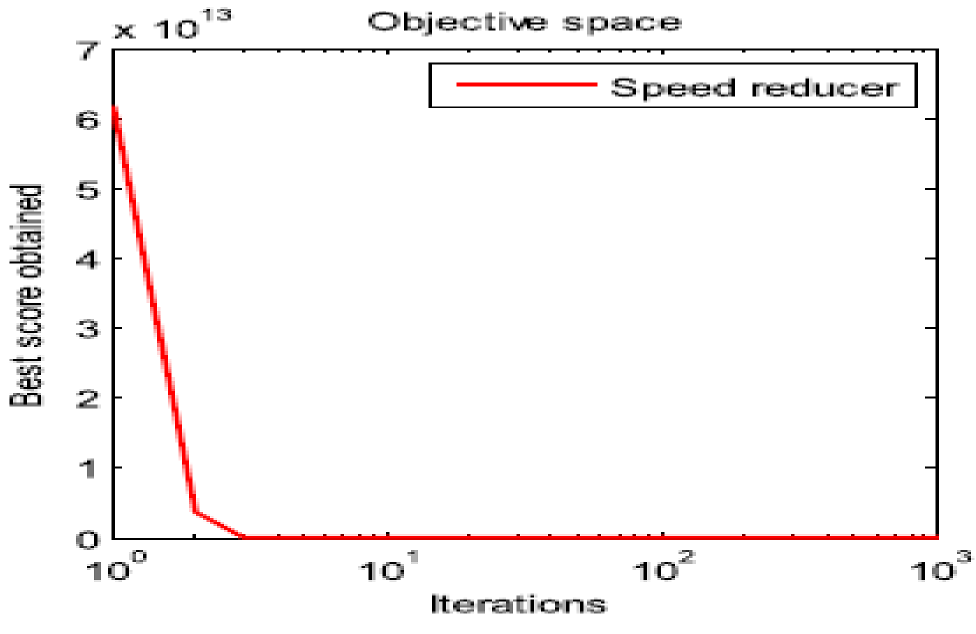

Figure 4.8 Speed Reducer Problems via Rat Swarm Optimization,

Specifically, [92] reveal that Rat Swarm Optimizer, when compared to all other optimizers, can get the closest ideal results. The recommended Rat Swarm Optimizer method is found to be the best optimizer among optimizers throughout the analysis of the results.

Rat Swarm Optimization can address several HD-challenging challenges and can handle many combinatorial optimization concerns, according to the results of the six real engineering formulation problems (COPs). Rat Swarm Optimization is an excellent optimization technique as a result since it has a low computational cost and merges quickly to the optimum. The uses of rat swarm optimization and its goal are depicted in the following figures.

4.6 Experimental Study

The Modified Rat Swarm Optimization inspired energy aware multi-hop routing method for WSN is developed in this work. Finding the best pathways to base stations (BS) in a clustered WSN is one of the main goals of the modified rat swarm optimization-inspired energy-aware multi-hop routing approach. Cluster heads (CHs) are created initially from the nodes and are chosen using a weighted clustering technique. The modified rat swarm optimizer multi-hop routing with a sense of energy (MRSO-MHR) technique then generates a fitness function for the routing process that has three input parameters: leftover energy, distance, and nodal degree. Levy movement ideas were included in the conventional RSO algorithm to create the MSRO approach. The MSRO-MHR technique's experimental results are analyzed, and the results are looked at from a variety of angles. The simulation results show the MSRO-MHR technique to have a prospective advantage over current state-of-the-art methods.

In Tab. 4.3 and Fig. 4.9 a detailed network lifetime assessment of the MSRO-MHR model using current techniques is carried out. The experimental results suggested that the MSRO-MHR approach had produced effective results with increased network lifetime values across all nodes. For example, the MSRO-MHR method achieved a superior network lifetime of 26.12 min with 100 nodes, whereas the Multi-level clustering and routing that is completely distributed energy aware (CDE), Optimal Multi-path Routing Protocol for Saving Energy (OMRPE), and Protocol for multi-path routing with Wolf optimization (WMPR), methods achieved inferior network lifetimes of 22.39 min, 21.10 min, and 21.36 min, respectively. While the CDE, OMRPE, and WMPR, approaches achieved decreased network lifetime of 19.95 min, 20.01 min, and 19.21 min, the MSRO-MHR model achieved an increased network lifetime of 24.01 min with 200 nodes. It is clear from the aforementioned tables and graphs that the MSRO-EAMHR model was used to develop an efficient WSN routing protocol.

Number of Nodes	Multi-level clustering and routing that is completely distributed energy aware	Optimal Multi-path Routing Protocol for Saving Energy	Protocol for multi-path routing with Wolf optimization	Modified Rat Swarm Optimizer
100	22.39	21.1	21.36	26.12
150	20.1	21.99	19.98	25.11
200	19.95	20.01	19.21	24.01

Table 4.3 Analysis of the RSO technique's network lifespan in comparison to existing methods

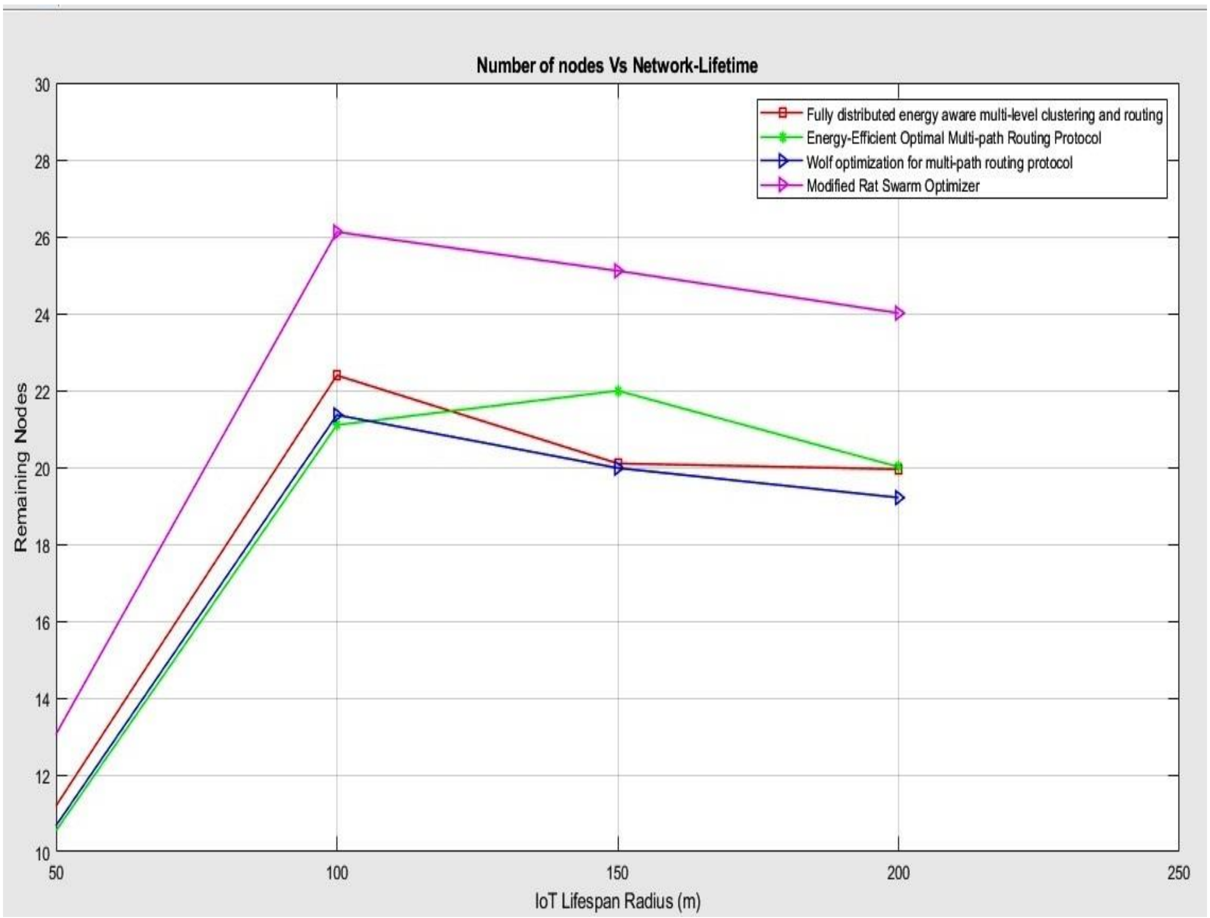

Figure 4.9 IoT Lifespan Radius Vs Remaining Nodes

4.7 Application of ROA & its objectives

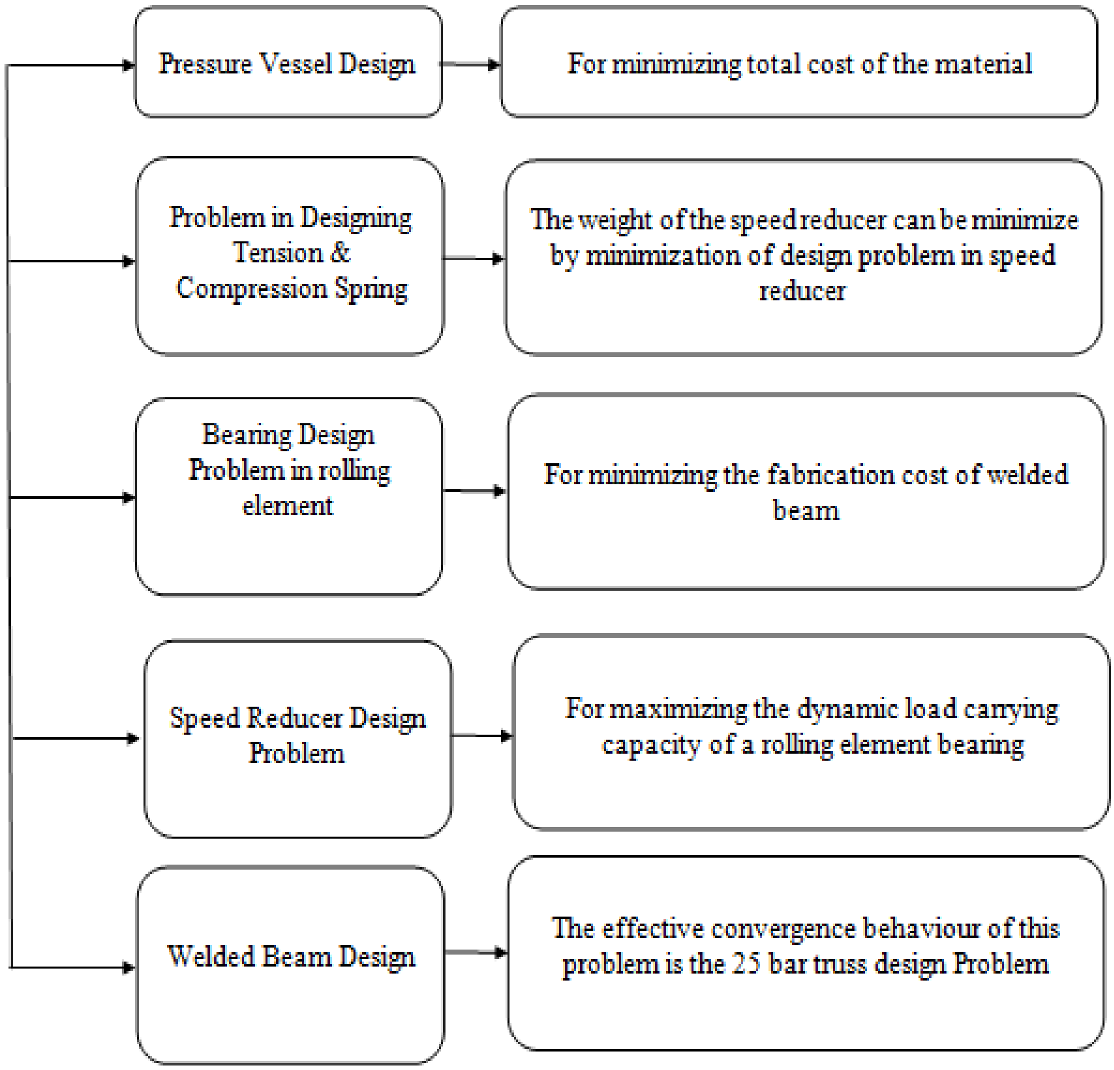

Figure 4.10 Use of ROA and its goals

When designing engineering issues, the Rat Swarm Optimisation (RSO) Algorithm is specifically designed to meet certain objectives. Let's examine how RSO relates to the goals of the study, which include improving energy efficiency, expanding coverage, decreasing redundancy, and prolonging life:

4.7.1 Increasing Life Expectancy:

Devices and components in engineering systems have limited functioning lifetimes. RSO can be used to maximise the use and upkeep of these parts, guaranteeing that their lifespans are increased by effective functioning and less wear and tear.

RSO increases engineered systems' total longevity by reducing needless stress on components and optimising their use.

4.7.2 Cut Down on Redundancy:

In an engineering system, redundant processes and parts can result in inefficiencies and higher expenses. Redundancy in engineering system design and operation can be found and removed with the use of RSO's optimisation technique.

RSO makes sure that the design and engineering solutions are simplified, minimizing needless duplication and complexity, through cooperative decision-making among swarm agents.

4.7.3 Expanding the Reach:

When discussing engineering difficulties, coverage frequently refers to the breadth and efficacy of a solution. The placement of sensors, actuators, or other components can be optimised with RSO to maximise coverage and efficacy.

RSO's adaptive and self-organizing characteristics enable it to dynamically modify component placement and configuration to attain ideal coverage under various conditions.

4.7.4 Efficiency of Energy:

Energy efficiency is a crucial factor to take into account while designing and running engineering systems. The flexibility and decentralised decision-making of RSOs can be used to optimise energy use in a variety of components.

RSO helps engineers solve energy-related challenges by controlling the energy consumption of components or devices in an intelligent manner.

4.7.5 Overall Integration: Rat swarm optimisation (RSO) incorporates ideas from the collective behaviours of rats into engineering systems. Swarm agents' cooperative decision-making and flexibility help to achieve the predetermined objectives in the engineering and operation of designed solutions.

4.7.6 Technical Approach: Based on the collective behaviours of rat swarms, the RSO Algorithm uses a decentralised, self-organizing methodology. Swarm agents cooperate and communicate to make choices that optimise the engineering and design solutions as a whole and support the objectives of the study.

4.7.7 Future Points to Remember:

The RSO Algorithm for creating engineering problems is still being researched. It may need to be further customized for particular applications, validated in a variety of engineering settings, and its efficacy in practical applications investigated. When it comes to solving optimisation problems in engineering design, RSO is a promising method because of its collective intelligence and flexibility.

4.8 LIMITATIONS OF MAYFLY ALGORITHM TO GO FOR RAT SWANN ALGORITHM

Like every optimisation technique, the Mayfly technique has drawbacks that could lead academics to look at different strategies like the Rat Swarm Algorithm. The following Mayfly Algorithm drawbacks may prompt one to take the Rat Swarm Algorithm into account:

Restricted Capability to Adjust to Changing Conditions:

The Mayfly Algorithm might find it difficult to adjust swiftly to environments that are dynamic and changeable. When the fitness landscape is subject to frequent and erratic changes, the adaptability of the Mayfly Algorithm may not be sufficient.

Trade-offs between Exploration and Exploitation:

research of recognised promising regions and solution space research are typically delicately balanced in optimisation problems. It may be difficult for the Mayfly Algorithm's mechanism to strike the best trade-off between exploration and exploitation.

Managing Activation Landscapes with Noise:

The Mayfly Algorithm may have trouble telling the difference between noise-filled fluctuations and real gains when there is noise present in the fitness assessments. In noisy or unpredictable circumstances, this may result in less-than-ideal convergence.

Speed of Convergence and Early Convergence:

The Mayfly Algorithm may suffer with premature convergence or converge too soon, depending on the type of optimisation problem. As a result, it may miss out on finding better solutions.

Problems with Scalability in High-Dimensional Spaces:

When dealing with high-dimensional optimisation problems, the Mayfly Algorithm's performance may deteriorate. The search space may become more dimensional, making it more difficult for the algorithm to successfully explore and exploit.

Agents' Reliance on Communication:

Swarm intelligence, which entails agent collaboration and communication, is the foundation of the Mayfly Algorithm. The algorithm's performance might be affected in situations when communication is difficult, expensive, or impracticable.

Insufficient Variety in Solutions:

The variety of solutions may be limited by swarm-based algorithms, such as the Mayfly Algorithm, which may converge to a certain area of the solution space. When a variety of options are preferred, this could be a disadvantage.

If the advantages of the Rat Swarm Algorithm outweigh the noted drawbacks of the Mayfly Algorithm, then switching to it might be a possibility. In some circumstances, the Rat Swarm Algorithm—which is renowned for its decentralised design, flexibility, and capacity to function in dynamic environments—might provide answers to some of the problems raised by the Mayfly Algorithm. The features of the optimisation problem and the algorithm's aptitude for resolving noted restrictions are frequently taken into consideration by researchers when selecting algorithms.

4.9 Limitations of RSO

Like any optimisation algorithm, the Rat Swarm Algorithm has its limitations even though it provides some benefits. These constraints may lead scientists to suggest hybridised algorithms as a way to get around certain obstacles. The following are some of the Rat Swarm Algorithm's drawbacks:

Constrained Investigation in Large-Scale Environments:

It can be difficult for swarm algorithms, such as the Rat Swarm Algorithm, to efficiently explore high-dimensional solution spaces. If the task is complicated and involves a lot of variables, the algorithm might not be able to sufficiently examine the whole space.

Availability to Early Convergence Risk:

When the algorithm chooses a less-than-ideal answer before fully examining the solution space, this is known as premature convergence. There is a chance that the Rat Swarm Algorithm will prematurely converge and produce worse than ideal outcomes.

Initial Configurations' Sensitivity:

The Rat Swarm Algorithm's performance, like that of many other optimisation methods, can be affected by the swarm's starting setups. In some cases, the convergence and output of the algorithm might be strongly influenced by the initial parameter selection.

Managing Noisy Fitness Landscapes Can Be Difficult:

The Rat Swarm Algorithm may face difficulties in noisy or stochastic fitness landscapes, when there are random fluctuations in the fitness function evaluations. It could be difficult for the algorithm to discern between noise and real advancements in the solution.

Issues with Scalability:

In large-scale optimisation problems, the scalability of swarm algorithms, such as the Rat Swarm Algorithm, may be an issue. The effectiveness and convergence speed of the technique may decrease as the size of the solution space rises.

Restricted Capability to Adjust to Changing Conditions:

It's possible that the Rat Swarm Algorithm won't adjust to the dynamic changes in the optimisation field very rapidly. The adaptability of the algorithm might be a constraint in situations where the fitness landscape changes over time.

Agents' Reliance on Communication:

Swarm-based algorithms frequently depend on cooperation and communication between agents. The algorithm's effectiveness can be impacted in situations when communication is difficult or restricted.

Researchers may suggest hybridised algorithms that combine the advantages of complementing methods with the capabilities of the Rat Swarm Algorithm in order to overcome these constraints. To improve the Rat Swarm Algorithm's performance in certain situations, hybrid approaches may incorporate the algorithm with machine learning strategies, other optimisation techniques, or problem-specific heuristics. The objective is to develop a more resilient and adaptable algorithm that can get beyond the drawbacks of using different optimisation strategies.

4.10 Conclusion

The foldable report of the Rat Swarm Optimizer algorithm will serve as an inspiration for future study. A future input for several multi-objective optimization issues will also be observed as the evolution of this Rat Swarm Optimizer approach.

In this chapter, the Rat Swarm Optimizer is introduced, which is an optimization system based on narrative swarm intelligence (RSO). The proposed Rat Swarm Optimizer algorithm's exploitation and exploration phases are assessed using different benchmark test functions to prevent the local optimum [80]. Particularly, researchers have looked at the computational problems associated with time and space concerns as well as merging activity. Parallelly, a unique MSRO-MHR algorithm for the energy-efficient WSN was developed to select the optimum pathways to base station. One of the primary aims of the MSRO-MHR approach is to maximise energy efficiency and network lifetime in WSN. The MSRO-MHR method uses weight clustering for initial cluster heads selection and cluster development. Furthermore, the MRSO algorithm with fitness function is employed to choose an optimal set of routes. The Levy movement idea is used to modify the regular RSO algorithm in the design of the MRSO algorithm. The experimental results of the MSRO-MHR approach are examined from several perspectives. According to the simulation findings, the MSRO-MHR approach has a potential benefit over existing state-of-the-art methodologies. Future data aggregation approaches are being developed in order to improve WSN energy efficiency even more.

CHAPTER -5
HYBRIDIZED MAYFLY AND RAT SWARM OPTIMIZER ALGORITHM (Hyb-MOP- MFRS)

CHAPTER -5

HYBRIDIZED MAYFLY AND RAT SWARM OPTIMIZER ALGORITHM (Hyb-MOP- MFRS)

5.1 Introduction

Due to 5G uses, IoT devices are now becoming more and more necessary in 5G networks. The Internet of Things (IoT) range problem and the issue of huge nodes will be solved by the development and widespread use of 5G networks. In this chapter, a parallel implementation of the hybridized Mayfly and Rat Swarm Optimizer algorithm with Hadoop is suggested for improving IoT range and node reliability in IoT with huge nodes, which automatically lengthens IoT lifespan. To reduce the problem scale, parallel operation first divides the IoT coverage difficulty caused by large nodes into several smaller problems, which are then solved using parallel Hadoop. Here, the mayfly mating and flying behavior are used to optimize the coverage problem. Rats' behavior for pursuing and attacking is used to solve the redundant problem. Next, choose the non-critical nodes wisely from the crucial nodes. Finally, parallel operation successfully overcomes the coverage issue of the IoT through big nodes by purposefully delaying the IoT lifespan. The NS2 tool is used to simulate the suggested technique. Analysis is conducted using key metrics such as computation time, energy efficiency, lifespan, and remaining nodes. In comparison to other methods, such as the parallel genetic algorithm to spread the lifespan of the internet of things on 5G networks (MPGA-IoT-5GN) and the energy-efficient topology control algorithm with graph convolutional network to expand the longevity of the internet of things on 5G networks and cloud radio access network to spread the lifespan of internet of things on 5G networks (CRAN- IoT-5GN), the proposed MOP-Hyb-MFRS-IoT-5GN method achieves lower computation time as higher lifetime.

The development and use of 5G networks present new opportunities and difficulties for IoT applications [92]. IoT habit sensor nodes have power sources that are intermittently interrupted. Therefore, covering IoT longevity is a constant problem [93]. Connecting more sensor nodes in the monitoring area and allowing them to alternate between the active and sleeping modes is the most likely solution to this issue [94]. High-frequency, short-range radio is used in 5G networks to communicate and achieve the fastest possible transmission speed [95]. Thus, 5G networks enhance the quantity of base stations linked to 4G networks. In 4G networks, each base station (BS) houses an in-charge access to the network processor

[96]. The network server is frequently accessed at the beginning of the process to achieve indigenous IoT [97]. On the other hand, a 5G network with reduced manufacturing costs reduces the access network gateway under BS [98]. It takes over the management of these network access servers in its stead [99]. As a result, data centers successfully implement a sizable IoT that is made up of several small-scale nodes [100]. Meanwhile, the 5G network promotes IoT adoption and leads to more IoT devices [101]. IoT contribution confronts new opportunities and problems as 5G networks gain popularity and scale [102]. IoT sensor nodes frequently lack constant power sources. Spreading the IoT lifetime is a significant issue as a result. The only solution for the power supply adding additional sensor nodes to the observing area is the issue [103]. An IoT conformation of active nodes lasts for one timeframe. Then, a different node on the next conformation becomes active for the new period [104]. The setup continues to generate a sequence while using worker nodes till IoT drains the clusters and the remaining nodes are unable to achieve the lower bound of the IoT range. [105]. IoT lifetime is therefore the same for complex configuration arrangements in operating nodes. The series of optimization methods in 5G networks is calculated to prolong the IoT's life before problems with huge nodes arise [106].

The IoT coverage problem, which was formerly NP-complete and addresses challenging massive-node scenarios routinely outside of the capacity of existing algorithms, is the choosing problem for clusters of coverage-centric dynamic [107]. These algorithms frequently demand that a series of potential solutions be reserved to examine the overall optimal solutions [108]. To solve a large process with huge implications, a count of potential solutions is required. Due to its inability to complete calculations after a longer time, this method fails. There are now three requests for the method that was developed to address the IoT coverage issue in massive-node scenarios. This approach can initially tip the scales and guarantees that the computations that are bounded by time constraints are finished. Additionally, in solving the multi-objective programming issue with the IoT coverage problem [109], as a result, the algorithm must consider internet connectivity and node severance as well as the effect of working nodes in the current configuration on future configurations. Finally, the process of solving an algorithm's internal optimization problems may quickly shift in the way of potential solutions.

5.2 Tool for Simulation-Network Simulator-2 (NS-2)

The event-driven simulation tool known as Network Simulator (Version 2), or NS2, has proven useful in researching the complex nature of network technologies. Using NS2, it is possible to simulate both functions and protocols for both wired and wireless networks (such as routing algorithms, TCP, and UDP). In general, NS2 provides users with a method for specifying various network protocols and simulating associated behaviour. The two main programming languages used in NS2 (OTcl) are Object-oriented Tool Command Language and CCC.

5.2.1 Configuring a Windows-Based compact Network simulation

Available simulation software called NS2 is available. It functions on a variety of operating systems, including Windows, Mac, and UNIX (or Linux). Unsurprisingly, given that NS2 was created in the Host machine, installation and operation there are both the easiest. A little updating is needed to operate NS2 on 64-bit operating systems. In essence, the goal is to resemble the features and functions of the Linux environment on Windows-based computers. Ubuntu is well-known software that accomplishes this task. After getting Ubuntu to function, the Unix-based installation process can be followed. It is advised to utilize the compact package for installation simplicity.

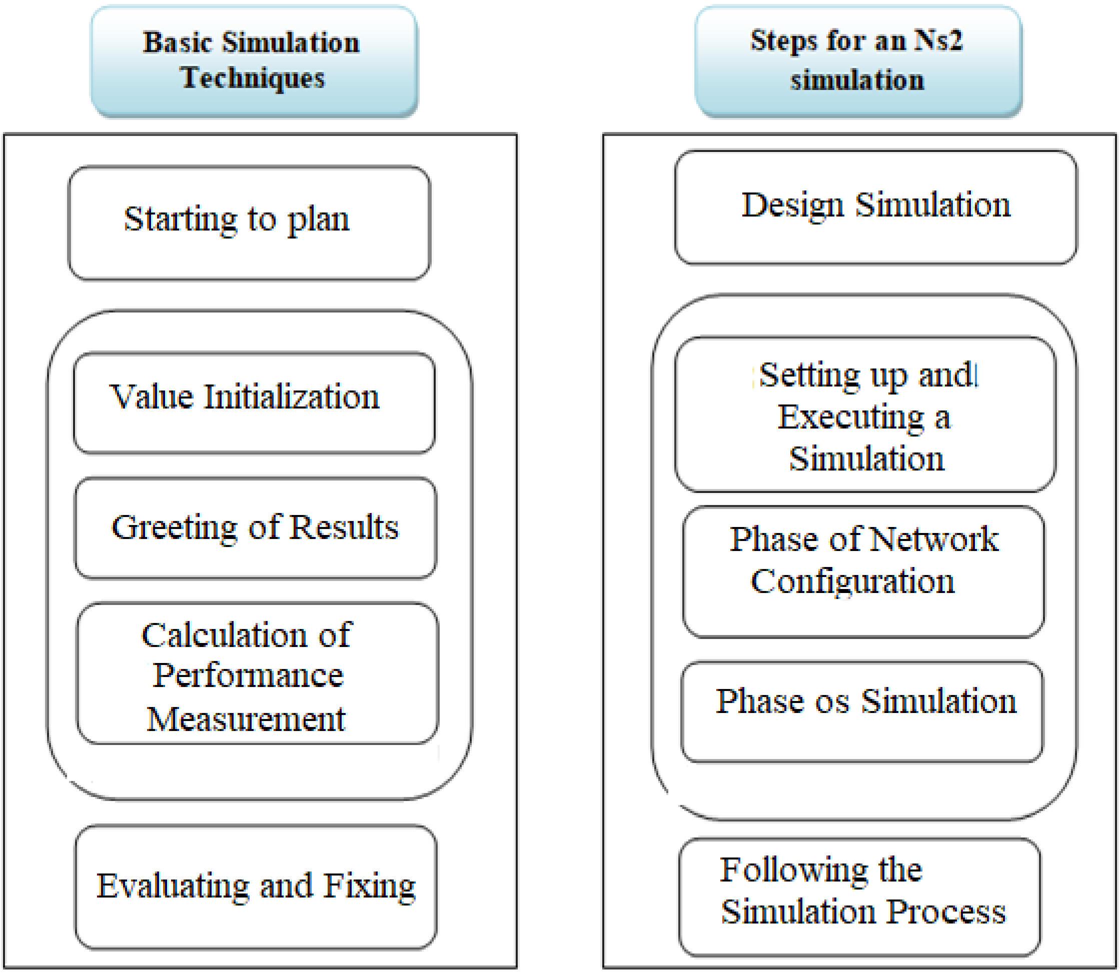

Figure 5.1 contrast of general simulation stages and NS2 simulation steps

5.2.2 The NS2 Simulation stages.

The generic simulation stages may be modified to operate with the NS2 framework, as illustrated in Fig. 5.1 Included in the main NS2 simulation steps are the following:

Step 1: Design the simulation designing the simulation is the initial stage in simulating a network. The simulation's objectives and network administration should be decided by the users.

Step 2: Setting up and Executing the Simulation the first stage's design is put into practice in this phase. It is divided into two stages:

• The phase of network configuration involves the creation and configuration of network elements (such as nodes, TCP, and UDP) following the simulation design. Additionally, certain events, including data transmission, have start times set.

• Simulation Phase: The simulation that was set up during the Complete Network Phase is now running. It keeps track of the simulation's timer and carries out events in reverse order. The simulation clock typically continues during this phase until it hits a predetermined value that was set in the complete network phase.

Post-simulation processing is step three. Verifying the program's integrity and assessing the effectiveness of the virtual network are the major objectives in this stage. While the second task is accomplished by properly gathering and compiling simulation results, the first task is known as debugging

5.2.3 Characteristics of Network Simulator 2

1. It is a network research distributed simulator.
2. It offers extensive assistance for simulating several protocols, including TCP, FTP, UDP, https, and DSR.
3. Both wired and wireless networks are simulated.
4. It is mainly based on UNIX.
5. Its scripting language is TCL.
6. Object-oriented support with Otcl
7. Tclcl: Linking C++ and OTCL
8. A discrete timetable of events

5.2.4 Simulation of wireless sensor networks in NS2 and Matlab

A Simulink network can build with numerous sink or ground station access points and sensor nodes using the NS2. Based on the specifications in the primary TCL configuration file, the arrangement of the sensor nodes varies in the simulation. Varied protocols, such as 802.11, 802.16, 802.15.4, IR-UWB, etc., as well as various connection and sensing range standards, as well as a different energy model depending on the number of poles specification, are used to determine the configurations. Utilize the ns2 that may design to transmit a packet message over a network with specified usages. The sensor nodes' location is specified during construction either randomly or deterministically.

Design and simulation of a wireless sensor network using MATLAB can be done. Utilize the communication toolkit set to generate a full WSN system model in the MATLAB and SIMULINK tools throughout the network topology creation and simulation procedure. When simulating a network, MATLAB can be used to model the communication channel, incorporate the default hardware design of sending nodes, and simulate the architecture of receiving nodes. The dynamic user-specified settings cannot be used in MATLAB/SIMULINK simulation. The simulation process in MATLAB and SIMULINK using the built-in default configuration tools can be created.

5.2.5 More Appropriate Tool for Simulation

In comparison to MATLAB, The wireless sensor network process can be performed using the ns2 simulation tool. Since the NS2 is among the tools that fully support network simulation. A network experiment with a dynamic setup of all sink nodes using the NS2 can be built. However, dynamic user-defined configurations when using MATLAB can't able to use. The simulation process in MATLAB and SIMULINK using the built-in default configuration tools can be created. Therefore, NS2 is the most suited user-friendly simulation software for the wireless sensor network when compared to MATLAB.

5.2.6 Execution steps of NS2 for Proposed work:

1. Go to the tcl folder then proposed the following tcl files

```
cd /code/tcl
```

2. Execute the tcl file proposed.tcl as

```
ns proposed.tcl
```

3. To view the output,

```
nam out.nam
```

Graph Generation steps

Based on Nodes

----
4. In the proposed, set the initial Node as 100

set opt(nn) 100, 150 and 200

To view the graphs

----

1. Go to the graphs/Node/100 folder and execute the following tcl files as,
   ns LifeTime.tcl
   ns RemainingNodes.tcl
   ns ComputationTime.tcl
   ns EnergyEfficiency.tcl
   ns Lifespan.tcl
2. Go to the graphs/Node/150 folder and execute the following tcl files as,
   ns LifeTime.tcl
   ns RemainingNodes.tcl
   ns ComputationTime.tcl
   ns EnergyEfficiency.tcl
   ns Lifespan.tcl
3. Go to the graphs/Node/200 folder and execute the following tcl files as,
   ns LifeTime.tcl
   ns RemainingNodes.tcl
   ns ComputationTime.tcl
   ns EnergyEfficiency.tcl
   ns Lifespan.tcl

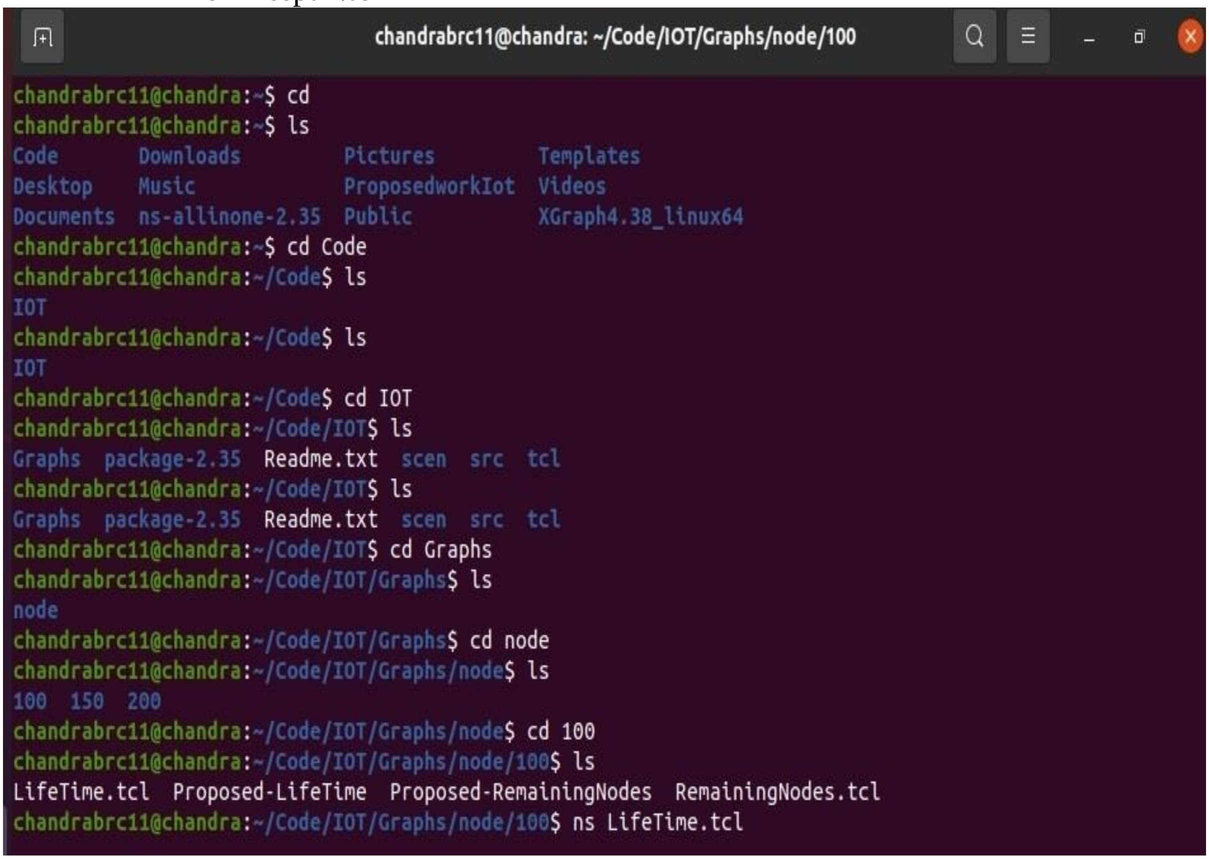

Figure 5.2 Execution steps of NS-2 simulator in UBUNTU

5.3 Hybridized Mayfly and Rat Swarm Optimizer algorithm

In this section, a parallel implementation of the Hybridized Mayfly and Rat Swarm Optimizer algorithm (MOP-Hyb-MFRS-IoT-5GN) is suggested to determine the ideal configuration structure for the Internet of Things with large nodes, thereby extending the IoT's useful life. Figure 1 shows a block diagram of the proposed MOP-Hyb-MFRS-IoT-5GN method. The in-depth presentation of the Parallelly Implemented Hybrid Rat Swarm and Mayfly Optimizer method for Multi-Objective Effective Coverage and Redundancy Persuasion Below is a Hadoop programming paradigm for IoT in a 5G network.

The Internet of Things (IoT) devices are made up of many nodes, some of which are crucial and others that are not. The non-critical nodes are impacted by the critical nodes in this situation, causing networks to experience convergence and redundancy issues with IoT devices. One of the key issues with building IoT devices is the network coverage issue. The coverage values must be raised or must exceed the specified threshold value. By expanding the coverage area, the quality of the services can be guaranteed to meet IoT needs (QoS). Below is the formulation of the IoT coverage model:

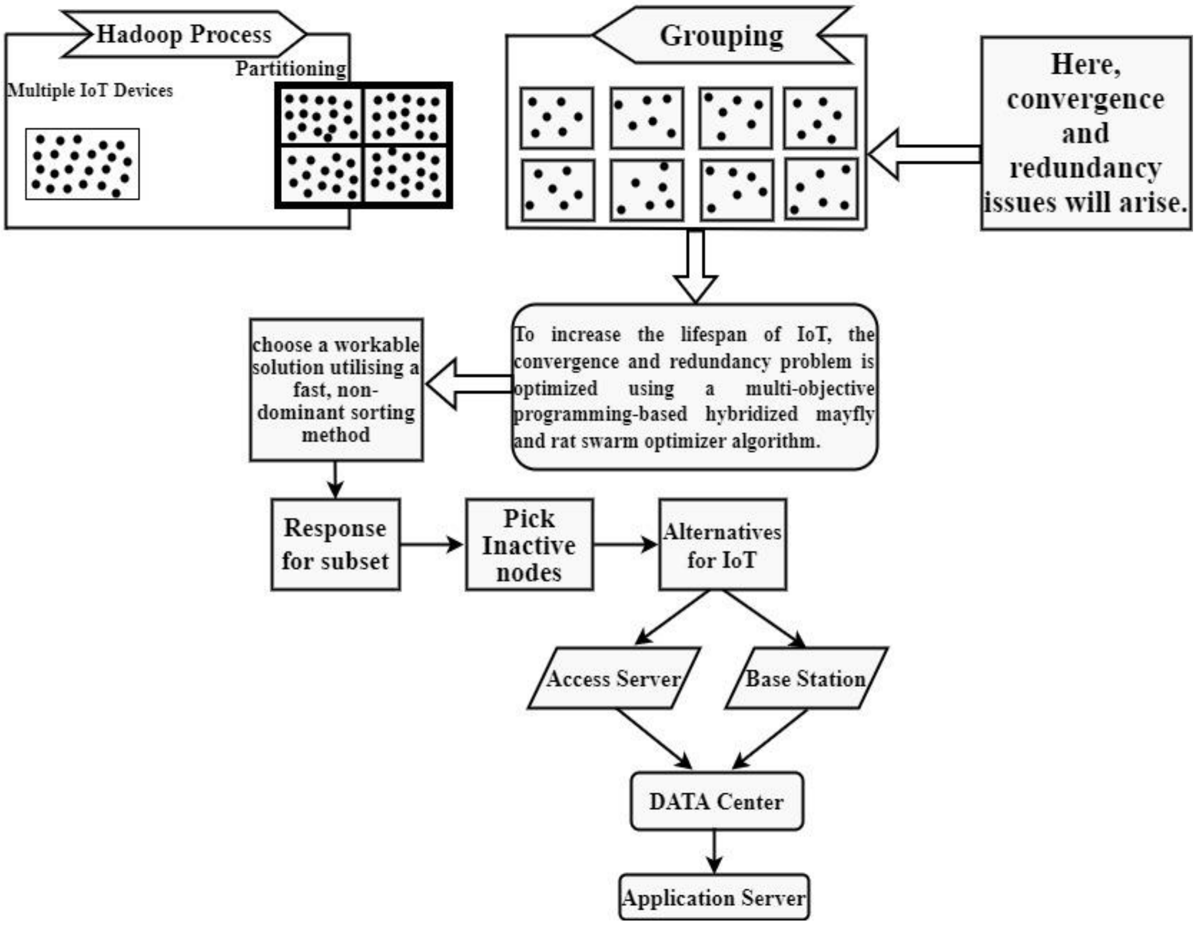

Figure 5.3 Block diagram of proposed MOP-Hyb-MFRS-IoT-5GN method

Every grid is 1nx1n if an IoT device operates in the monitoring region *X* and its area is denoted by *nxm* grids. Let r_i be the number of i^{th} sensor nodes. In the Internet of Things, num represents the node's count. $R= (r_1,r_2,.......,r_i,....r_{num})$ specifies the sensor node set. Then, each node's location is shown as (a_i,b_i) represents the node's coordinate, and (a_i,b_i,s) stands for the node's real perception circle. Where the node $r_i(a_i,b_i)$ designates the center and s the radius guessing that the perception radius s_d is at least twice as large as the communication radius, or $sd>=2s$. In this way, sensor nodes take care of the monitoring aspect, while IoT keeps connected. Let the criteria for the sensor node $r_i(a_i,b_i)$ to cover the grid (a,b) defined by the equation $Q_{cov}(a,b,r_i)$ be the connectedness (1).

$$Q_{\text{cov}}(a,b,r_i) = \begin{cases} 1, & (a-a_i)^2 + (b-b_i)^2 \leq s^2 \\ 0, & else \end{cases} \tag{1}$$

$$Q_{\text{cov}}(a,b,r_i) = \begin{cases} 1, & \ni r_i \in D_j, Q_{\text{cov}}(a,b,r_i) = 1 \\ 0, & else \end{cases} \tag{2}$$

In addition, consider $Q_{cov}(a,b,D_j)$ to be the grid-covering conditions for the j_{th} working nodes. The equation expresses these values as follows: where R signifies all active nodes and D_j identifies the subdivision node of the set (2). Once a node r_i reaches the jth working node configuration, it fulfills equation (1) and IoT includes (a,b) grid monitoring. The matrix count that covers the D_j configuration is specified by *X* area (D_j), and it is written as follows:

$$X_{area}(D_j) = \sum_{a=1}^{n}\sum_{b=1}^{m} Q_{\text{cov}}(a,b,D_j) \tag{3}$$

As a result, the convergence problem in IoT devices with a coverage rate of j^{th} working nodes configuration $S_{cov}(D_j)$ defines matrix count that is enclosed by the active nodes arrangement D_j by dividing the entire number of grids in the monitoring region, and its equation is provided in equation (4).

$$S_{coverage}(D_j) = \frac{\sum_{b=1}^{n}\sum_{b=1}^{m} Q_{\text{cov}}(a,b,D_j)}{n \times m} \tag{4}$$

Then, using equation (5), the excess is determined

$$S_{redudancy}(D_j) = \frac{\sum_{a=1}^{n}\sum_{b=1}^{m} Q_{red}(a,b,D_j)}{n \times m} \tag{5}$$

The rate of redundancy is calculated using equation (5). The ideas presented earlier are incompatible, and the so-called unidentified optimum solution is represented by just one objective variable. The sensor network that is required for various solutions is regarded as the crucial node. The equation then contains the redundancy with settings (6)

To ensure the quality of service, the coverage rate must remain above the cutoff mark (QoS), If the grid is redundantly covered by active nodes in the D_j arrangement, then let Q_{red} *(a, b, D_j)* be the criteria *(a; b).*

$$Q_{red}(a,b.D_j) = \begin{cases} 1, & C_{\text{cov}}(a,b,D_j) > 1 \\ 0, & else \end{cases} \tag{6}$$

Equations (4) and (5) above describe the range and redundancy issues with IoT devices, and the Hyb-MFRS algorithm is used to reduce these issues.

Therefore, it is challenging to solve the issue with coverage for IoT using several nodes on networks using 5G. The initial perception region of a sensor node is significantly less than the monitoring area of an IoT, which means that if the node is active, it only impacts the local area rather than the entire globe. This is one of the challenges with the IoT. As a result, it is possible to partition the IoT into several zones (also known as sub-IoT) and address their coverage issues concurrently [122]. Second, in over-deployment and alternative node activation scenarios, IoT has a large number of redundant nodes. The Hybridized Mayfly and Rat Swarm Optimizer Hyb-MFRS method are used to resolve the aforementioned issues, and it is suggested that employing huge nodes on 5G networks would extend the lifespan of IoT.

An abbreviated version of the Parallelly Implemented Hybrid Rat Swarm and Mayfly Optimizer method's algorithm is provided below:

5.3.1 Parallel Hybrid Optimisation for IoT Systems Algorithm

Enter:

Environmental information

Initial setup of the gadget

Parameters for optimisation

Result:

Optimum distribution of devices

Modular redundancy arrangement

Methods of Algorithm:

Set up the IoT system:

Put environmental data in.

Configure the gadget initially.

Establish the optimisation criteria.

Processing in parallel:

Partition the optimisation assignments for simultaneous execution.

Mayfly Algorithm: A Parallel Approach

For every concurrent IoT device:

Use the Mayfly Algorithm to optimise dynamic coverage.

Adapt device positions to changing environmental conditions.

Rat Swarm Optimizer: A Parallel Approach

For every concurrent IoT device:

For multi-objective optimisation, use Rat Swarm Optimizer.

Enhance communication and redundancy protocols.

Optimal Hybridization:

Combine the outcomes of the Mayfly and Rat Swarm to achieve balanced goals.

Use machine learning to make predictions and adaptive learning

Enhancing Energy Efficiency:

Reduce energy usage by optimising gadget operations.

Utilise machine learning in conjunction with adaptive energy management

Rat Swarm Decentralised Control:

Give devices the ability to use swarm intelligence to make local decisions.

Put self-healing systems in place to ensure fault tolerance.

The Integration of Machine Learning:

Examine past information to forecast future circumstances.

Give gadgets the ability to change on the go using machine learning models.

Adaptive Load Distribution:

In order to avoid congestion, divide the load among the devices.

Make sure it's scalable by using distributed load balancing techniques.

Synchronous Optimisation:

Consistently maximise a number of goals

Increase coverage while lowering energy usage.

Boost redundancy without sacrificing effectiveness

Systems of Adaptive Control:

Incorporate mechanisms for adaptive control

Allow gadgets to notice and adjust to changes in their surroundings

Assure resilient and flexible behaviour in reaction to changing circumstances.

Outcome Findings:

Optimum distribution of devices

Modular redundancy arrangement

Finish Algorithm

This technique uses the Mayfly and Rat Swarm algorithms to provide a high-level overview of the procedures required in parallel hybrid optimisation for Internet of Things systems. It's crucial to remember that, depending on certain system needs and external factors, the actual implementation may entail more intricate procedures and considerations.

5.4 Mayfly and Rat Swarm Optimizer algorithm hybridized with Mapping-Reduce Process in Parallel

Here, the lifespan of IoT employing huge nodes on 5G networks is extended using the parallel implementation of the Hybridized Mayfly and Rat Swarm Optimizer method. The vast IoT, which consists of several little IoTs equal to base stations, in 5G networks, which replace access point processors under base stations as the network's management entity. The massive IoT is divided into multiple smaller IoTs by partitioning procedures in the data center. If a sub-IoT still has a lot of nodes, the data center undertakes clustering operations on each sub-IoT. Finally, the method uses a non-critical node preference selection strategy to control how the worker nodes are currently configured. Hadoop is used in this task to estimate working node settings for every cluster of nodes concurrently. Current worker node configurations that are workable solutions ought to avoid selected essential nodes. Due to the absence of crucial nodes, the final configuration won't be able to change the lower bound of coverage if these essential nodes go down too soon. The Hyb-MFRS technique is then applied to estimate the working node settings for each set of nodes in parallel while separating the essential nodes from the IoT devices. The Mayfly and Rat Swarm optimization algorithms are combined to form the Hyb-MFRS algorithm.

The mayfly optimization technique integrates the main benefits of evolutionary algorithms and swarm intelligence to solve optimization problems utilizing mayfly flying behavior and mating behavior [123]. The Rat Swarm optimization technique combines the key advantages of swarm intelligence and evolutionary algorithms to solve difficult optimization problems by mimicking the hunting and attacking actions of rats [124]. To address the issues of coverage and redundancy in IoT devices, the combination of the mating behavior and flying behavior of mayflies with the pursuing and attacking behaviors of rats.

To distinguish the critical and non-critical nodes via the procedure of dividing and merging using the Hyb-MFRS algorithm, a large number of IoT mass devices are divided into sub-nodes using the mapping-reduce process. The size of the sub-IoT is first calculated from the enormous devices and then divided into several sub-IoTs by the Mayfly's flying behavior. In addition, each sub-IoT has a size that is 10 times smaller than the radius of perception, and the current sub-coverage appears to be impacted by nodes in nearby sub-IoTs. IoT However, an enormous sub-IoT with numerous nodes will result in a sharp increase in performance time. By employing the parameter M_{sub}, which stands for the count of sub-IoT partitioning, the mayfly flying behavior will thus optimize the coverage issue during the division process, and the mayfly mating process will shorten the execution time.

Second, the grouping issue in the vast IoT devices is resolved using the pursuing and attacking behaviors of rats, which also helps to lessen the redundancy issue when separating the critical nodes from the non-critical nodes. Let the number of nodes involved in the Hyb-MFRS algorithm's sub-grouping IoT activities be referred to as M_{grp}. The nodes in the sub-IoT are divided into M_{grp} groups here by the chasing behavior of the rat swarm algorithm till the grouping activities are terminated. After that, disperse the nodes across the sub-IoT at random. M_{time} in this case provides grouping operation times. If more optimal solutions exist after M_{time} times of clustering operations, the time forms M_{time}+1 specify durations of clustering operations to construct extra groups to cover those solutions.

By separating essential nodes from non-critical nodes and reducing the redundancy issue, the fitness functions of the Hyb-MFRS algorithm are utilized to increase the coverage area of IoT devices. Here, the redundancy problem is optimized using the pursuing and fighting behaviors of rats, while the coverage problem is optimized using the flying behavior and mating process of mayflies. The fitness equation is then stated in the equation to achieve the objective function equation (7).

$$\textit{Fitness function (objective)} = \textit{Max (IoT Coverage), Min (Redundancy)} \tag{7}$$

After that, there will be thorough discussions of the Hyb-MFRS Algorithm's use in differentiating important nodes from non-critical nodes to solve coverage and redundancy issues during partitioning and grouping, hence extending IoT lifespan.

5.5 Hyb-MFRS Algorithm Based on Multi-Objective Programming

In this, the IoT employing enormous nodes is separated into numerous sub-IoTs using the parallel method Hyb-MFRS, which is based on multi-objective programming. For each sub-IoT, the algorithm pools the nodes' operating hours to cover workable solutions. By doing this, the algorithm is given a list of node groups that it might potentially handle using its hybridized Mayfly and Rat Swarm Optimizer method. The strategy breaks down the IoT coverage challenge for big networks into multiple smaller issues using partitioning and pooling. To resolve coverage and redundancy issues, Figure 5.4 shows the flow chart for the hybridized Mayfly and Rat Swarm Optimizer algorithm. The Multi-Objective Programming-Based Hyb-MFRS Algorithm is used to separate and group data to handle coverage and redundancy concerns. Hyb-MFRS Algorithm and rapid non-dominated sorting are two phases of multi-objective programming that are used to optimize redundancy and coverage issues, particularly the selection of non-critical nodes. The sensor node that is required for a variety of possible solutions is thought to be the crucial node.

The algorithm can avoid choosing crucial nodes if it extracts the current configuration of operational nodes from the potential solutions. The number of essential nodes in the D_j configuration is therefore specified by M_{config} (D_j). M_{config} must be reduced using a hybridized Mayfly and Rat Swarm Optimizer built using multi-objective programming (D_j). Here, the mayfly mating and flying behavior are used to optimize the coverage problem. The size of the sub-IoT is calculated from the enormous devices and divided into multiple sub-IoTs using the mayfly's flying behavior. a single sub-IoT is also ten times smaller than the range of the perception, and nodes in neighboring sub-IoTs appear in order to affect the current sub-coverage IoTs when employing the parameter M_{sub}.

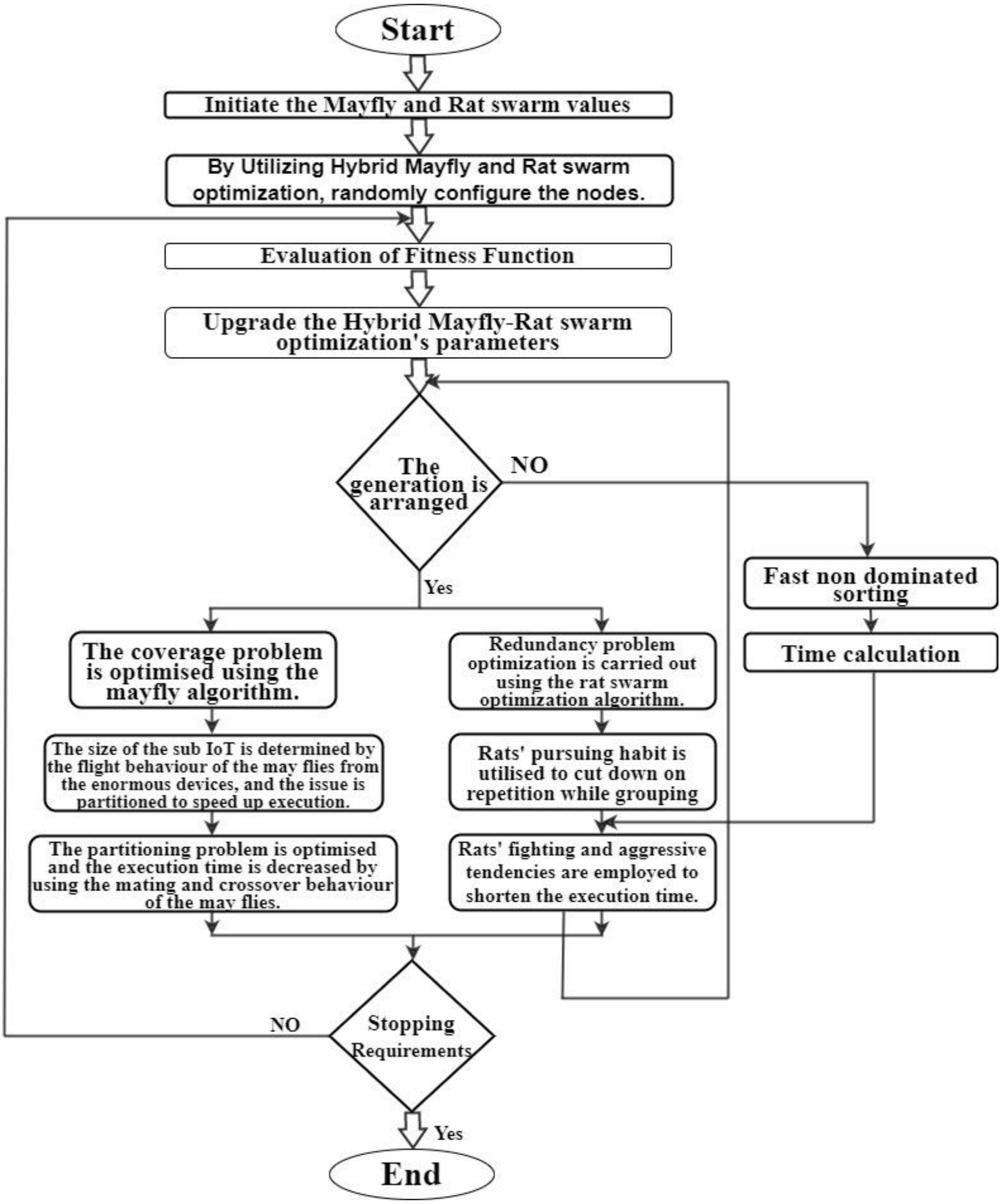

Figure 5.4 Flowchart for the Rat Swarm Optimize and Hybridized Mayfly algorithms

The present places of the may fly are set up as a sub-IoT partitioning. After that, the equation provides the coverage problem minimizing formula (8)

$$M_{best_j} = \begin{cases} M_{sub}^{time+1}, & if\ D\left(M_{sub}^{time+1}\right) < D\left(M_{best_j}\right) \\ is\,kept\,the\,same, & otherwise \end{cases} \tag{8}$$

The partitioning problem is then optimized and the execution time is decreased, making it simple to distinguish the crucial nodes from the non-critical nodes. This is done by using the mating or cross-over behavior of the Mayflies. When two mayflies mate, one parent is chosen to represent both the male and female populations, according to the crossover operator. Numerous flies are used to represent the nodes in this situation. Male nodes are chosen for critical nodes, while female nodes are chosen for non-critical nodes. The best nodes are then optimally chosen to choose new nodes as offspring. The selection of critical and non-critical nodes is provided in equation (9)

$$\begin{aligned} Newnode_1(off\ spring) &= D * critica\ln ode + (1-D) * noncritical \\ Newnode_2(off\ spring) &= D * noncritica\ln ode + (1-D) * critical \end{aligned} \tag{9}$$

The coverage problem is optimized in this case by representing D as the random values with configurations, which best separates, the crucial nodes from the non-critical nodes. Second, the grouping issue in the vast IoT devices is resolved using the pursuing and attacking behaviors of rats, which also helps to lessen the redundancy issue when separating the critical nodes from the non-critical nodes. Let M_{grp} be referred to as the number of nodes involved in the Hyb-MFRS algorithm's sub-IoT grouping activities. The nodes must be grouped after the critical nodes have been separated from the non-critical nodes; otherwise, a redundancy issue would arise during grouping, lowering system performance and lengthening processing time. When grouping, the rats' pursuing behavior is employed to eliminate duplication, and its equation is presented in equation (10)

$$M_{grp} = S_{red} - j \times \left(\frac{S_{red}}{Iteration_{\min imization}} \right), Where\ \ j = 0,1,2,...iteration_{\min imization} \tag{10}$$

Rats' fighting behavior is used in this way to decrease redundancy and shorten execution times. The system will experience a delay when more packets enter IoT devices, increasing the amount of time needed to identify the nodes. In this case, time is minimized by utilizing equation (11)

$$(M_{time} + 1)_j = |M_{time}(j) - M_{time}| \tag{11}$$

The coverage area is maximized and redundancy is decreased throughout the segmentation and clustering process by applying equation (11), which also reduces execution time and satisfies the goal function.

5.5.1 Fast Non-Dominated Sorting

To maximize coverage and redundancy, the Hyb-MFRS-quick non-dominated sorting algorithm employs fast non-dominated sorting. Assume that a_1 and a_2 are real. Then, a1 dominates a_2 and is superior to a_2 in all ways. A solution is referred to be a non-dominated solution if it does not dominate any of the other alternatives. The multi-objective programming is carried out via a non-dominated set search using the quick non-dominated sorting method. Let's say that m_q and MRq specify dominating the current q solution and a solution set to determine the amount of solutions, respectively. Then, every individual is specified by MRq after quick non-dominated sorting computes the m_q value. Fast non-dominated sorting in particular finds every person whose MRq is equal to zero and compares their coverage and redundancy to those of the current generation.

5.6 Merging Solutions for Total IoT

The Hyb-MF-RS method is implemented in parallel, and FNS is used to merge the solutions into smaller node groups and sub-IoT. FNS has all non-dominated solutions for search. In comparison to other solutions, A non-dominated approach offers either greater coverage or fewer redundancies. Consider $M_{fesiable}$ be the quantity of potential solutions set aside next to FNS. When a parallel algorithm completes (Mtime+1) times the number of groups of operations performed by a node on each sub-IoT, (Mtime+1) M_{grp} groups is created. Thus, it uses Hadoop to solve groups in parallel. As a result, during the iteration phase, the algorithm gathers all potential solutions for the (M_{time}+1) M_{grp} group. The solution is then sorted using a quick non-dominated sorting algorithm, which keeps the first Mfesiable solution. Each answer is held back to serve as the next solution set if the count is less than that Mfesiable. Additionally, the method compiles the remainder of M_{grp} solutions as a testing set. The method then utilizes the comparing solution sets to merge enter the solution set the test set. Next, merge two sub-IoT by creating the complete set of the ultimate IoT solution. To calculate the Cartesian product, the algorithm precisely mixes the potential answers from the two nearby sub-IoT.

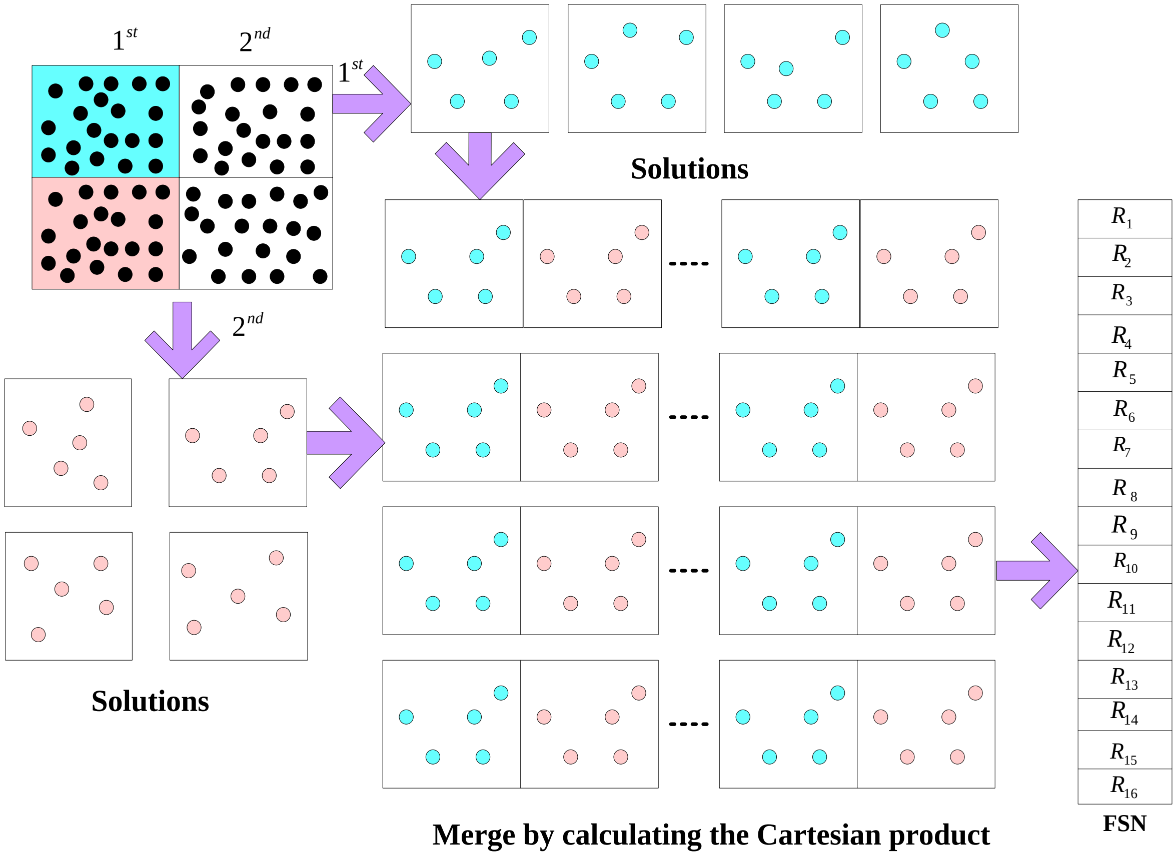

Figure 5.5 Integrating Total IoT solutions

The method uses FSN to sort the answers and then extracts the first answer as a solution set with merged IoT from the two sub-IoT. The technique generates 16 integrated IoT solutions for computing Cartesian products. Finally, the algorithm uses FSN to sort the solutions and keeps the first six solutions that it considers for the collection of solutions. Every sub-IoT is merged into the IoT as the process of merging progresses. The IoT as a whole then has a solution set thanks to this algorithm.

5.7 Selection of Non-Critical Nodes Preferentially

For establishing the current working node configuration, the parallel method accepts the second portion of MOP-Hyb-MFRS (which is the preferable option for non-critical nodes). Taking into account how the procedure will affect the current configuration in the next configuration additionally, it reduces the number of risky node needs. The threshold transforms a node into a critical node when the occurrence counts of the nodes increase. When using a parallel method, the whole IoT solution is combined with pre-made coverage and redundancy-based sorting solutions. MOP-Hyb-MFRS is included in each solution that is developed, regardless of the number of important nodes. The monitoring section is spread in the middle with dangerous nodes. As a result, MOP-Hyb-MFRS correctly identifies the essential nodes. Thus, the chosen topology effectively satisfies the three objectives of coverage, redundancy, and minimal critical nodes. As a result, Hyb-MFRS maximizes length in the configuration order for working nodes, extending the life of IoT.

5.8 Results and Discussion

Here, a parallel-implemented hybrid (MF-RS) multi-objective effective motivation of coverage and redundancy framework for IoTs in 5G networks is suggested, and its simulation performance is examined. The suggested system is implemented using NS2, an Intel i5 processor, and 4GB of RAM. The analysis in this section includes assessment criteria including compute time, energy efficiency, longevity, lifetime, and remaining nodes. Efficiency, computing time, energy efficiency, longevity, lifespan, and remaining nodes are some of the performance indicators that are examined. The 3 currently used approaches are contrasted with these measures in the proposed system. MPGA-IoT-5GN [113], EDTC-GCN-IoT-5GN [114], and CRAN-IoT-5GN [115] are the 3 approaches that are now in use. Table 5.1 lists the variables that were used in the simulations.

Table 5.1: simulated variables

Simulation parameters	**Values**
Monitoring area	$100m \times 100m$
Coverage bound	90%
Count of nodes	25
Perception radius	10m
Energy units in a node	10 J
Individual numbers in a generation	60
Maximum generations	100

5.8.1. Assessment Metrics

In this, the outcomes are calculated using a variety of performance indicators. The following calculations are made for the performance metrics:

5.8.2. Computation Session

Equation (9)'s expression for the percentage of the node, which is used to calculate computation time, is as follows:

$$Computation\,Time = \frac{Utilizing\ Time}{Nodes\,Rate} \tag{9}$$

5.8.3. Energy Savings

By dividing the energy acquired from the output by the original input energy, which is stated in equation (10) as follows, the energy efficiency of IoT in a 5G network is calculated.

$$Energy_{efficiency} = \frac{U_{out}}{U_{in}} \times 100\% \tag{10}$$

5.8.4. Lifespan

The lifetime value is calculated by multiplying the total node lifespan by the total number of nodes, which is given in equation (11).

$$Lifespan = \frac{sum\,of\ nodes\,lifespan}{number\,of\ nodes} \tag{11}$$

5.8.5. Lifetime

The lifetime parameter is calculated by multiplying the value of nodes by the average node's lifespan. It is provided as follows in equation (12):

$$LTV = Average\,Nodes\,Lifespan\ \times Nodes\,Value \tag{12}$$

5.9. Result and Discussion

5.9.1. Context 1: Node 100

In this part, the performance of data transmission over 100 nodes is examined. Figure 5.6-5.10 compares the simulation results for the suggested MOP-hyb-MFRS-IoT-5GN method with the existing methods, such as MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN-IoT-5GN, in terms of IoT Lifespan radius Vs. Computation Time, IoT Lifespan radius Vs. Energy Efficiency, IoT Lifespan radius Vs. Lifetime, and IoT

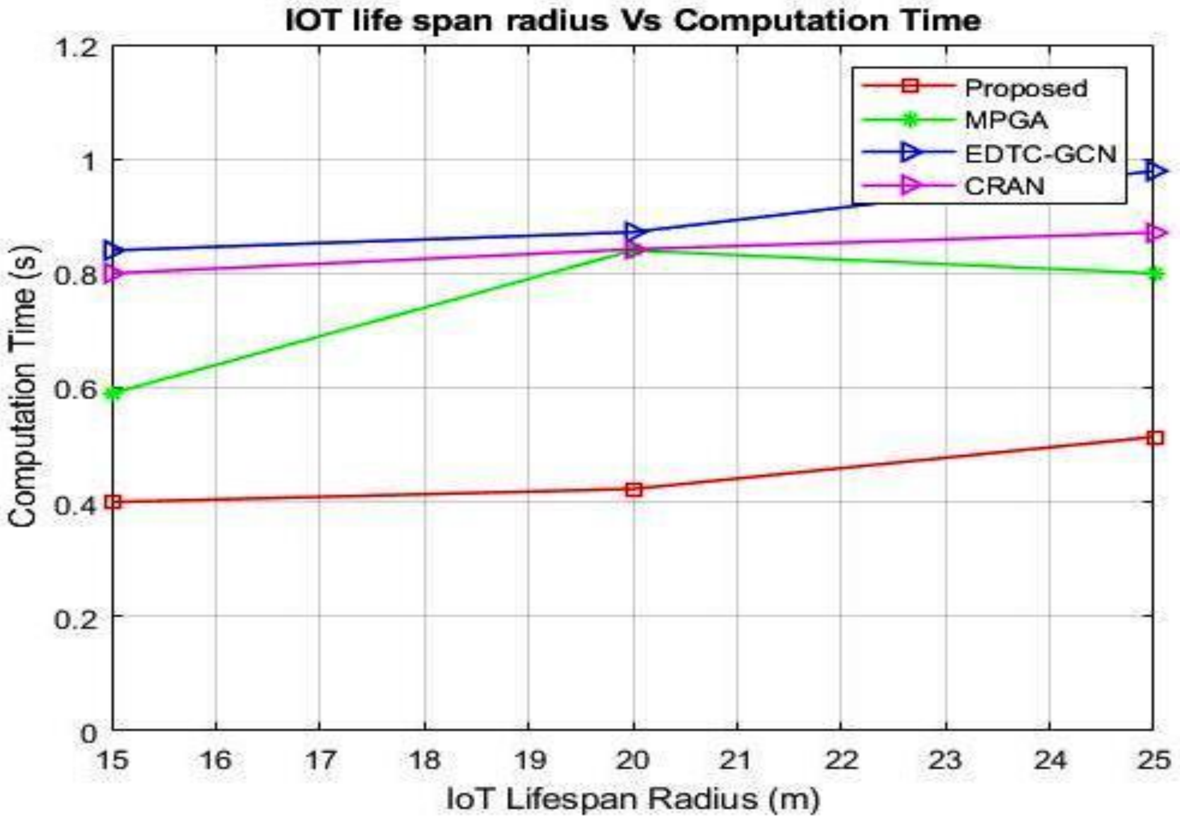

Figure 5.6 The IoT Lifespan Radius vs. Computation Time

The performance of IoT Lifespan radius vs. computation time is displayed in Figure 5.6.

The calculation time of the suggested MOP-hyb-MFRS-IoT-5GN method is 32.20%, 52.38%, and 50.00% faster at IoT Lifespan radius 15 compared to the MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN-IoT-5GN existing techniques, respectively.

The computation time of the proposed MOP-hyb-MFRS-IoT-5GN method is 37.97%, 51.49%, and 48.05% faster at IoT Lifespan radius 20 compared to the MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN-IoT-5GN existing techniques, respectively.

The calculation time of the suggested MOP-hyb-MFRS-IoT-5GN technique is 32.72%, 47.49%, and 40.98% less than the computation times of the MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN-IoT-5GN existing methods, respectively, at IoT Lifespan radius 25.

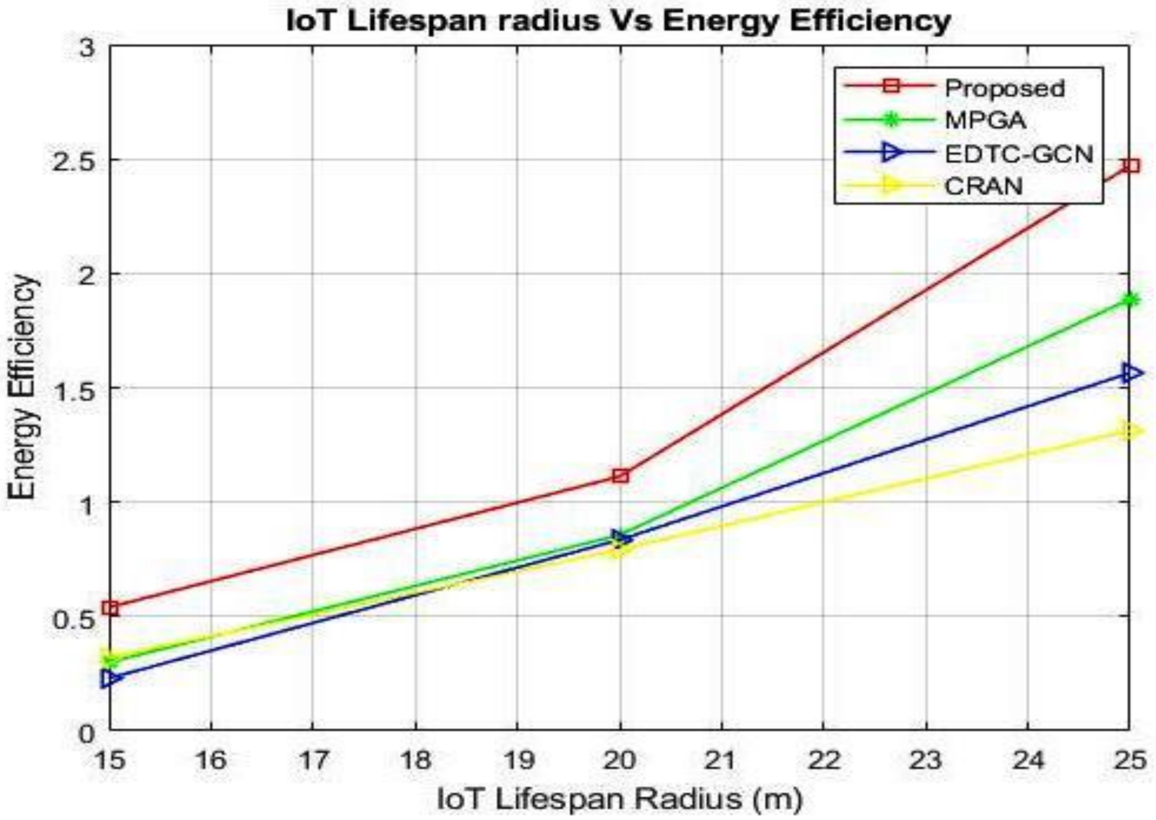

Figure 5.7 Energy Efficiency vs. IoT Lifespan Radius Performance

The relationship between IoT Lifespan Radius and Energy Efficiency is seen in Figure 5.7.

The suggested MOP-hyb-MFRS-IoT-5GN method's energy efficiency at IoT Lifespan radius 15 is 44.44%, 57.40%, and 40.74% greater than those of the current techniques, MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN-IoT-5GN, respectively.

The suggested MOP-hyb-MFRS-IoT-5GN technique offers energy efficiency at IoT Lifespan radius 20 that is 23.02%, 24.46%, and 28.77% greater than that of the current methods, MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN-IoT-5GN, respectively.

The suggested MOP-hyb-MFRS-IoT-5GN approach offers superior energy efficiency at IoT Lifespan radius 25 than the current methods, such as MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN-IoT-5GN, by 23.60%, 81.38%, and 46.88%, respectively.

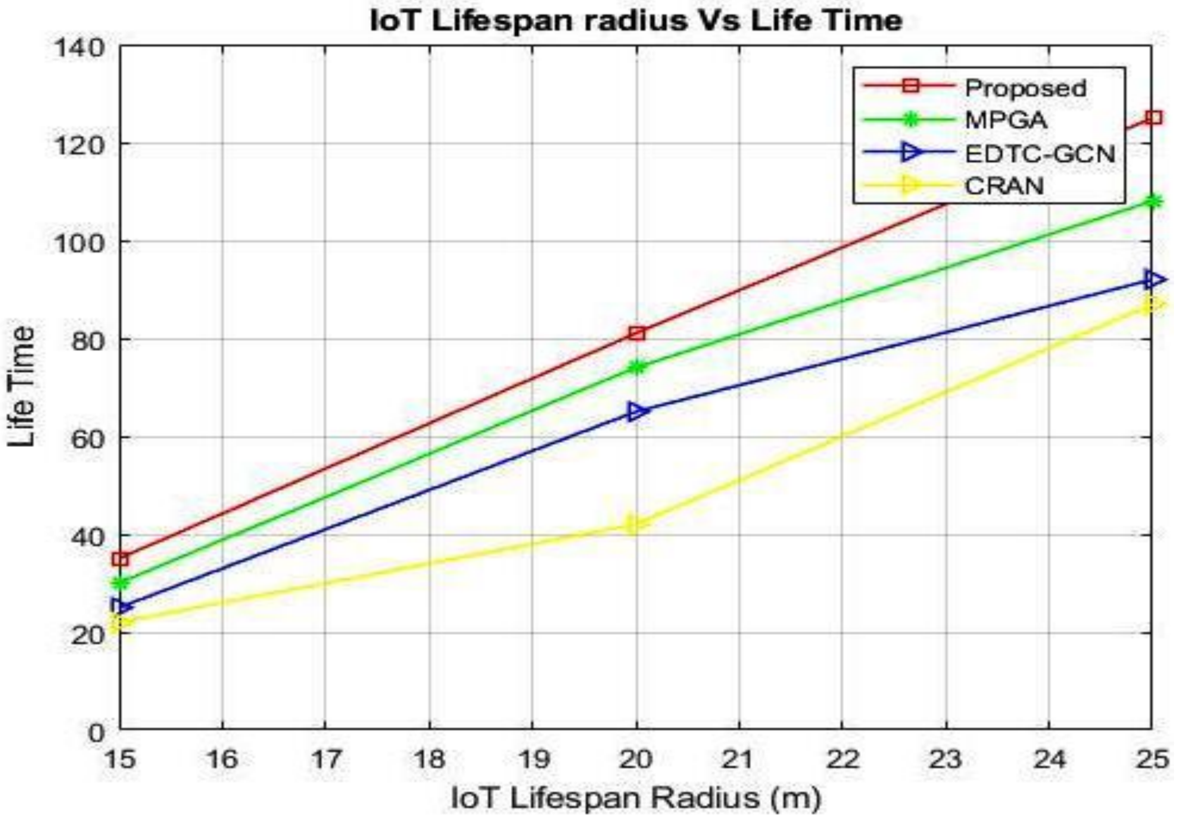

Figure 5.8 The Radius of IoT Lifespan Performance vs Life Time

Figure 5.8 shows the performance of IoT Lifespan radius Vs Life Time.

At IoT Lifespan radius 15, the Life Time of the proposed MOP-hyb-MFRS-IoT-5GN method provides 14.28%, 28.57%, and 37.14% higher Life Time compared with the existing methods like MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN- IoT-5GN respectively.

At IoT Lifespan radius 20, the Life Time of the proposed MOP-hyb-MFRS-IoT-5GN method provides 8.64%, 19.75%, and 48.14% higher Life Time compared with the existing methods like MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN- IoT-5GN respectively.

At IoT Lifespan radius 25, the Life Time of the proposed MOP-hyb-MFRS-IoT-5GN method provides 13.60%, 26.40%, and 30.40% higher Life Time compared with the existing methods like MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN- IoT-5GN respectively.

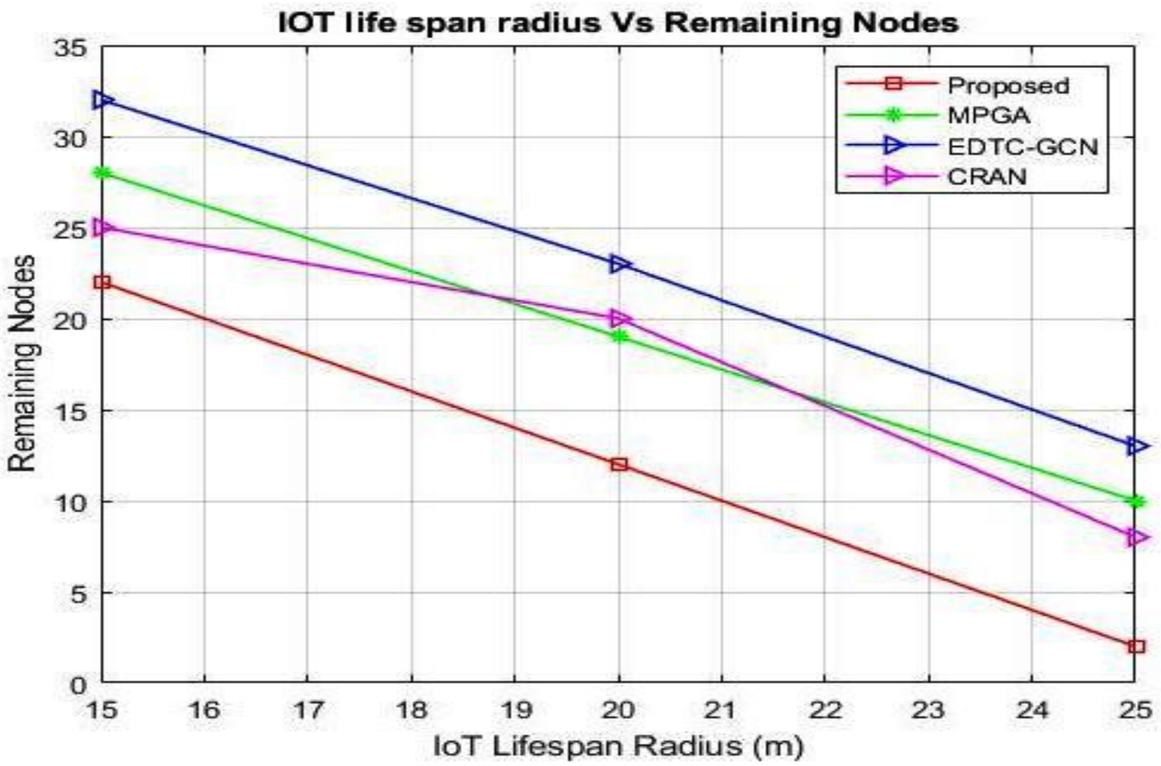

Figure 5.9 IoT Lifespan Radius Performances against Remaining Nodes

Figure 5.9 compares the IoT Lifespan radius performance to the other nodes.

When compared to current techniques like MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN-IoT-5GN, the remaining nodes of the suggested MOP-hyb-MFRS-IoT-5GN method give 27.27%, 31.25%, and 12.00% higher remaining nodes, respectively, at IoT Lifespan radius 15.

When compared to current techniques like MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN-IoT-5GN, the remaining nodes of the proposed MOP-hyb-MFRS-IoT-5GN method give 36.84%, 47.82%, and 40.01% higher remaining nodes at IoT Lifespan radius 20, respectively.

When compared to current techniques like MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN-IoT-5GN, the remaining nodes of the proposed MOP-hyb-MFRS-IoT-5GN method give 80.01%, 84.60%, and 75.01% higher remaining nodes, respectively, at IoT Lifespan radius 25.

Scenario1 Node 100

IOT life span radius Vs Computation Time

Life time Radius	proposed	MPGA	EDTC_GCN	CRAN
15	0.4	0.59	0.84	0.80
20	0.423	0.682	0.872	0.842
25	0.514	0.764	0.979	0.871

IOT life span radius Vs Energy Efficiency

Life time Radius	proposed	MPGA	EDTC_GCN	CRAN
15	0.54	0.3	0.23	0.32
20	1.112	0.856	0.835	0.792
25	2.470	1.887	1.565	1.312

IOT life span radius Vs LifeTime

Life time Radius	proposed	MPGA	EDTC_GCN	CRAN
15	35	30	25	22
20	81	74	65	42
25	125	108	92	87

IOT life span radius Vs Remaining Nodes

Life time Radius	proposed	MPGA	EDTC_GCN	CRAN
15	22	28	32	25
20	12	19	23	20
25	2	10	13	8

Table 5.2: comparison results of proposed with Different algorithms value for Node 100

5.9.2. Context 2: Node 150

In this part, the performance of data transmission over 150 nodes is examined. Figure 8-11 compares the simulation results for the proposed MOP-hyb-MFRS-IoT-5GN method with the existing methods, such as MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN-IoT-5GN, in terms of IoT Lifespan radius Vs. Computation Time, IoT Lifespan radius Vs. Energy Efficiency, IoT Lifespan radius Vs. Lifetime, and IoT.

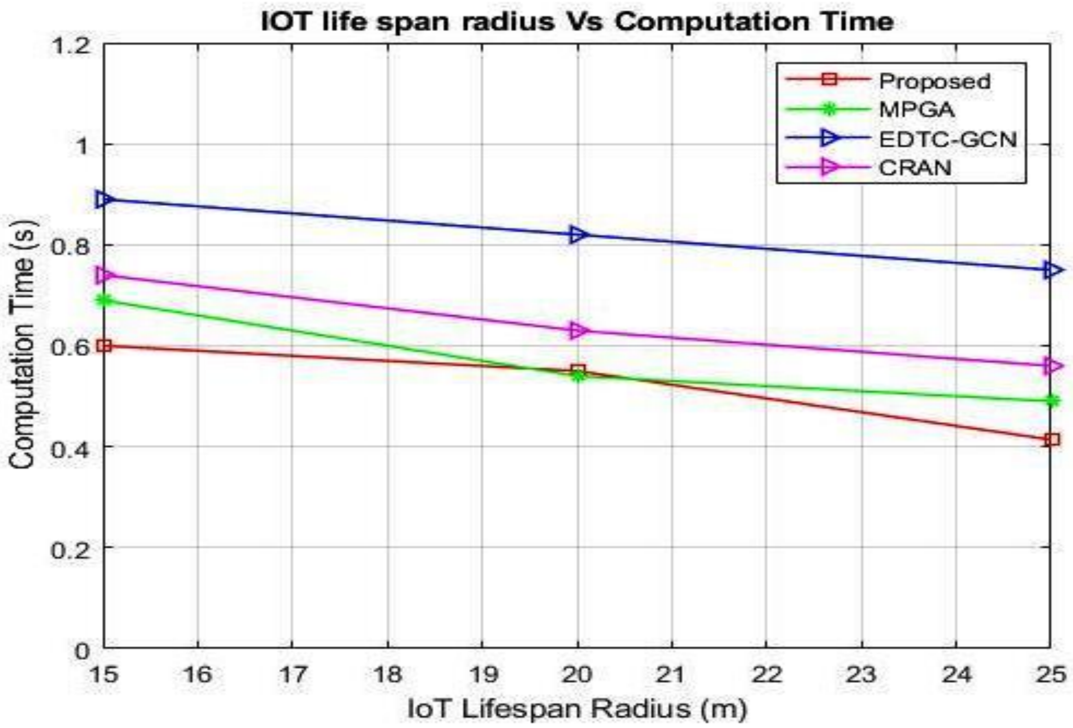

Figure 5.10 IoT Lifespan Radius Performance vs Computation Time

The performance of IoT Lifespan radius vs. computation time is displayed in Figure 5.10. The calculation time of the proposed MOP-hyb-MFRS-IoT-5GN method is 33.33%, 55.05%, and 15.85% faster at IoT Lifespan radius 15 compared to the MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN-IoT-5GN existing techniques, respectively.

The calculation time of the proposed MOP-hyb-MFRS-IoT-5GN method is 4.624%, 37.42%, and 18.35% less than that of the current techniques, MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN-IoT-5GN, respectively, at IoT Lifespan radius 20.

The calculation time of the suggested MOP-hyb-MFRS-IoT-5GN method is 15.85, 33.70%, and 24.86% less than the computation times of the MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN-IoT-5GN techniques, respectively, at IoT Lifespan radius 25.

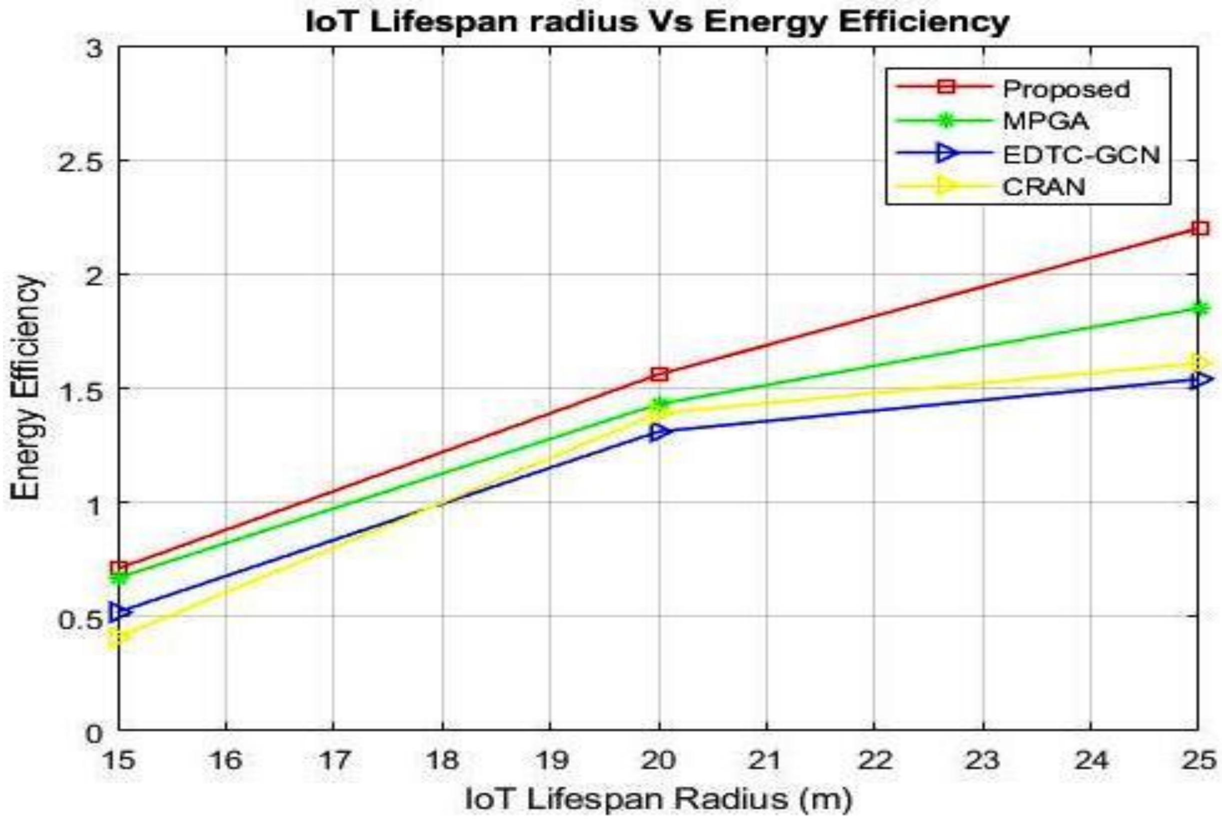

Figure 5.11 Energy Efficiency vs. IoT Lifespan Radius Performance

The relationship between IoT Lifespan Radius and Energy Efficiency is seen in Figure 5.11. In comparison to current techniques like MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN-IoT-5GN, the suggested MOP-hyb-MFRS-IoT-5GN approach offers greater Energy Efficiency at IoT Lifespan radius 15 by 5.60%, 26.76%, and 42.25%, respectively.

The suggested MOP-hyb-MFRS-IoT-5GN technique offers, respectively, 8.15%, 16.25%, and 17.94% greater Energy Efficiency at IoT Lifespan radius 20 than the current methods, MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN-IoT-5GN.

When compared to current systems like MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN-IoT-5GN, respectively, the energy efficiency of the proposed MOP-hyb-MFRS-IoT-5GN system achieves 18.18%, 29.98%, and 59.01% more energy efficiency.

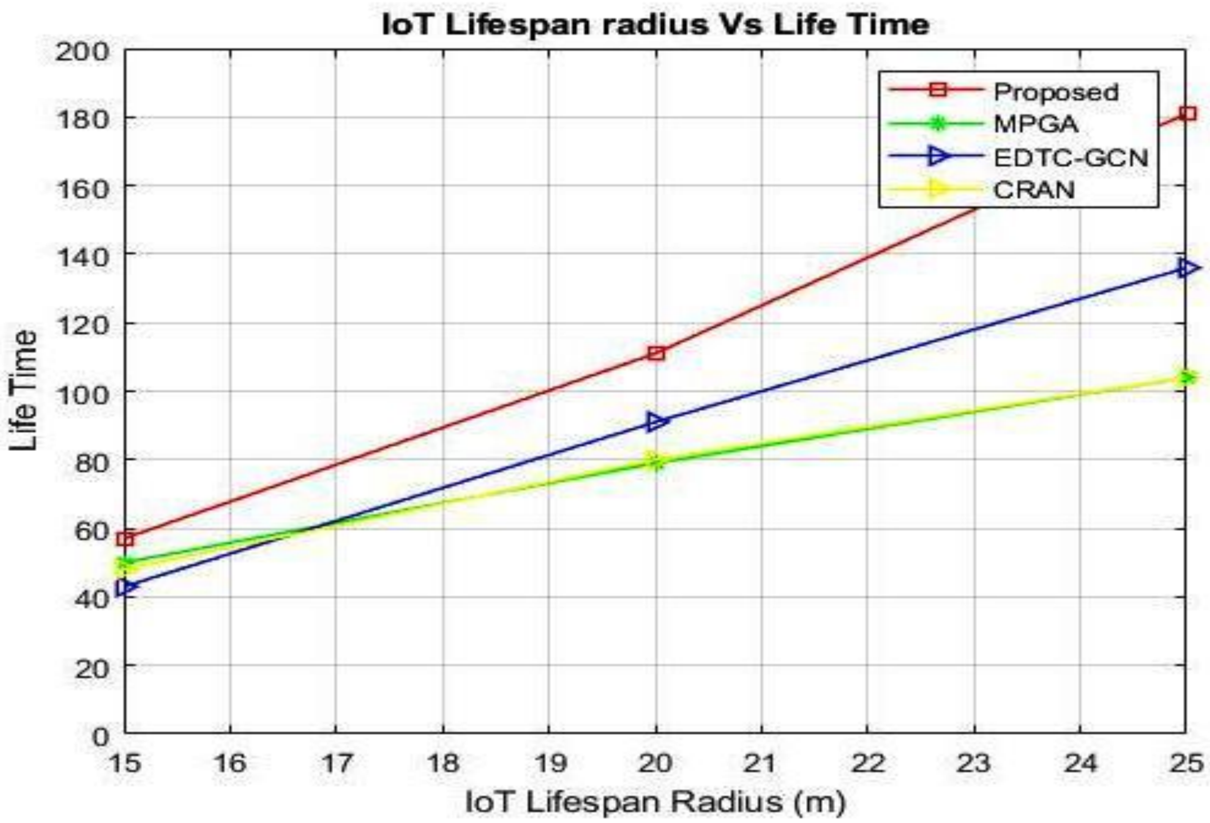

Figure 5.12 The IoT Lifespan Radius Performance vs Life Time

The performance of IoT Lifespan radius vs. Life Time is displayed in Figure 5.12.

The suggested MOP-hyb-MFRS-IoT-5GN technique offers a 12.28%, 28.83%, and 42.54% greater Life Time at IoT Lifespan radius 15 compared to the current methods, MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN-IoT-5GN, respectively.

The suggested MOP-hyb-MFRS-IoT-5GN technique has a Life Time that is 24.56%, 18.02%, and 24.86% greater than the current methods, MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN-IoT-5GN, respectively, at IoT Lifespan radius 20.

The life time of the suggested MOP-hyb-MFRS-IoT-5GN technique is 15.79%, 27.93%, and 42.54% greater at IoT Lifespan radius 25 than the life times of the MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN-IoT-5GN current methods, respectively.

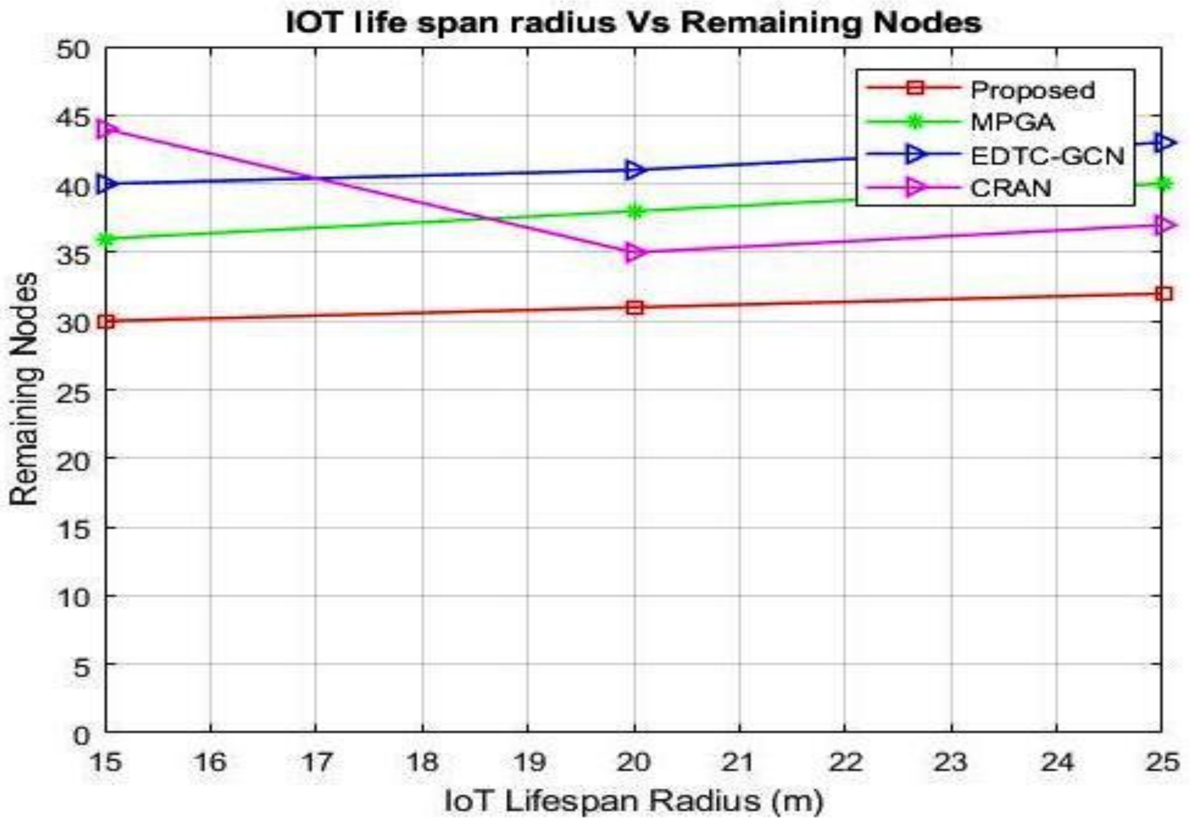

Figure 5.13 IoT Lifespan Radius Performances against Remaining Nodes

Figure 5.13 compares the IoT Lifespan radius performance to the other nodes.

When compared to current techniques like MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN-IoT-5GN, the remaining nodes of the proposed MOP-hyb-MFRS-IoT-5GN method give 16.67%, 25.01%, and 31.82% higher remaining nodes, respectively, at IoT Lifespan radius 15.

When compared to current techniques like MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN-IoT-5GN, the remaining nodes of the suggested MOP-hyb-MFRS-IoT-5GN method give 18.42%, 24.39%, and 11.43% higher remaining nodes, respectively, at IoT Lifespan radius 20.

When compared to current techniques like MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN-IoT-5GN, the remaining nodes of the proposed MOP-hyb-MFRS-IoT-5GN approach give respectively 20.01%, 25.58, and 13.51% higher remaining nodes.

Scenario2 Node 150										
IOT lifespan radius Vs Computation Time						IOT lifespan radius Vs Energy Efficiency				
Life time Radius	proposed	MPGA	EDTC_GCN	CRAN		Life time Radius	proposed	MPGA	EDTC_GCN	CRAN
15	0.6	0.6	0.89	0.74		15	0.71	0.67	0.52	0.41
20	0.516	0.541	0.822	0.632		20	1.563	1.435	1.309	1.288
25	0.414	0.492	0.751	0.551		25	2.200	1.863	1.540	1.672
IOT lifespan radius Vs LifeTime						IOT lifespan radius Vs Remaining Nodes				
Life time Radius	proposed	MPGA	EDTC_GCN	CRAN		Life time Radius	proposed	MPGA	EDTC_GCN	CRAN
15	57	50	43	48		15	30	36	40	44
20	111	79	91	80		20	31	38	41	35
25	181	104	136	104		25	32	40	43	37

Table 5.3: comparison results of proposed with Different algorithms value for Node 150

5.9.3. Context 3: Node 200

In this part, the performance of data transmission over 200 nodes is examined. Figure 12-15 compares the proposed MOP-hyb-MFRS-IoT-5GN method with existing methods like MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN-IoT-5GN. The simulation results for IoT Lifespan radius vs. Computation Time, IoT Lifespan radius vs. Energy efficiency, IoT Lifespan radius vs. Lifetime, and IoT Lifespan.

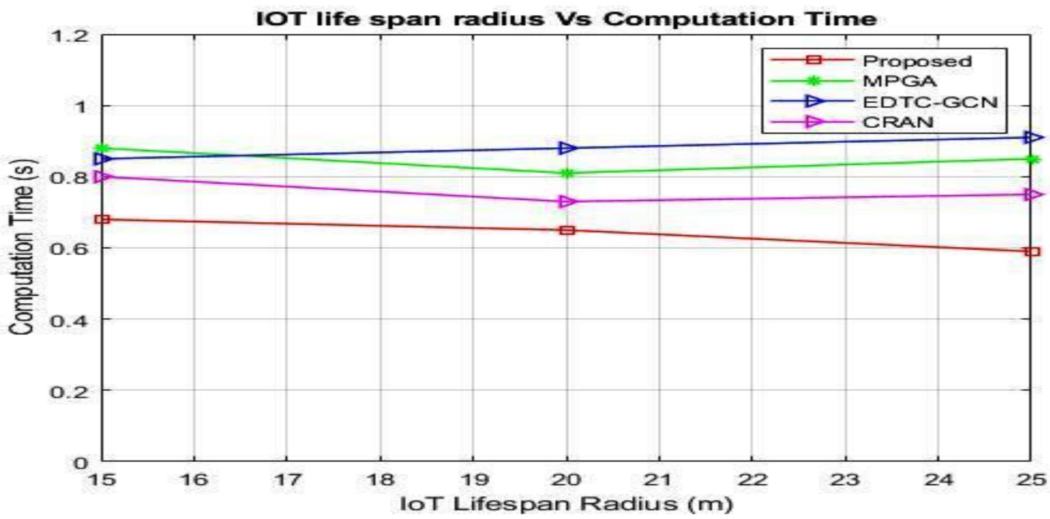

Figure 5.14 IoT Lifespan Radius vs Computation Time

The performance of IoT Lifespan radius vs. computation time is displayed in Figure 5.14.

The calculation time of the proposed MOP-hyb-MFRS-IoT-5GN method is 22.73%, 20.01%, and 15.11% faster at IoT Lifespan radius 15 compared to the MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN-IoT-5GN existing techniques, respectively.

The calculation time of the suggested MOP-hyb-MFRS-IoT-5GN method is 19.28%, 25.46%, and 11.43% less than the computation times of the MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN-IoT-5GN techniques, respectively, at IoT Lifespan radius 20.

The calculation time of the suggested MOP-hyb-MFRS-IoT-5GN method is 30.04%, 35.24%, and 21.24% less than the computation times of the MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN-IoT-5GN techniques, respectively, at IoT Lifespan radius 25.

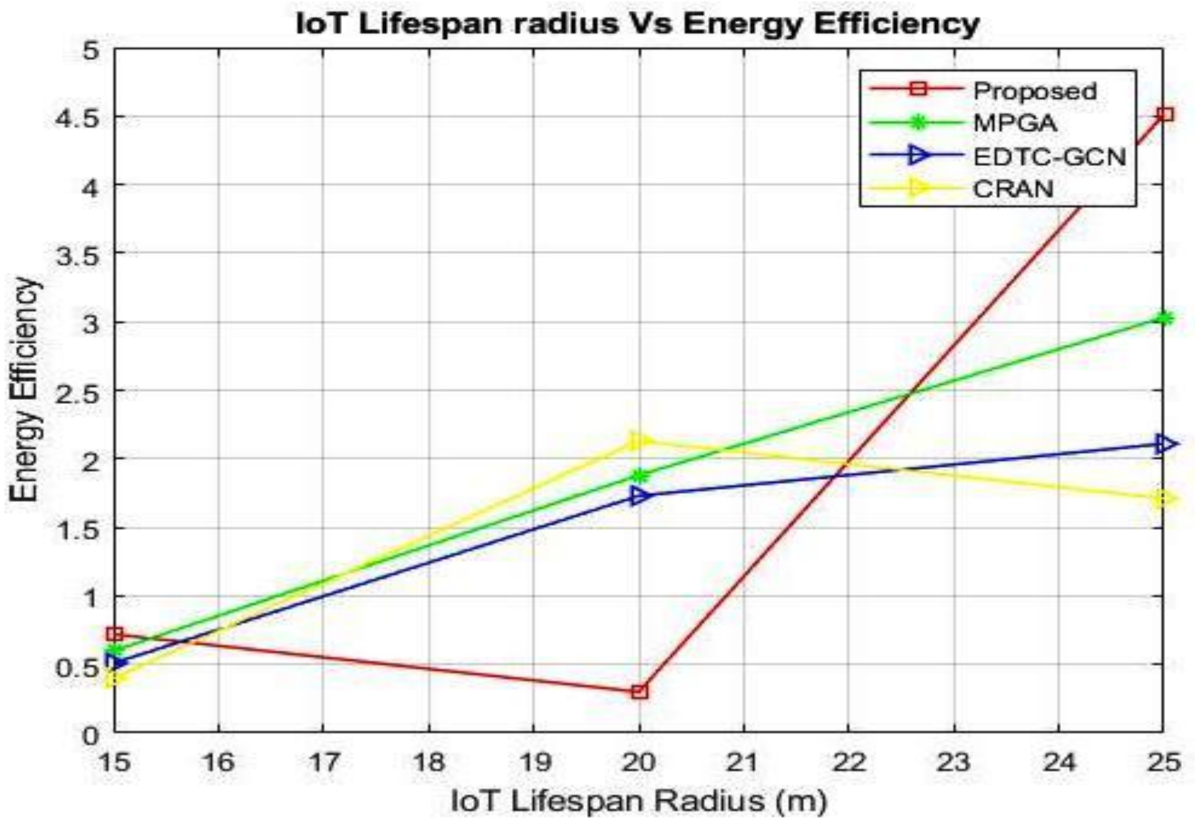

Figure 5.15 Lifespan Radius vs Energy Efficiency

The relationship between IoT Lifespan Radius and Energy Efficiency is seen in Figure 5.15. The suggested MOP-hyb-MFRS-IoT-5GN method's Energy Efficiency at IoT Lifespan radius 15 is 16.67%, 31.94%, and 44.31% greater than those of the current techniques, MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN-IoT-5GN, respectively.

In comparison to current techniques like MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN-IoT-5GN, the suggested MOP-hyb-MFRS-IoT-5GN approach offers 37.60%, 42.43%, and 29.18% greater Energy Efficiency at IoT Lifespan radius 20.

At IoT Lifespan radius 25, the suggested MOP-hyb-MFRS-IoT-5GN technique offers energy efficiency that is respectively 31.96%, 53.74%, and 62.53% greater than that of the current methods, MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN-IoT-5GN.

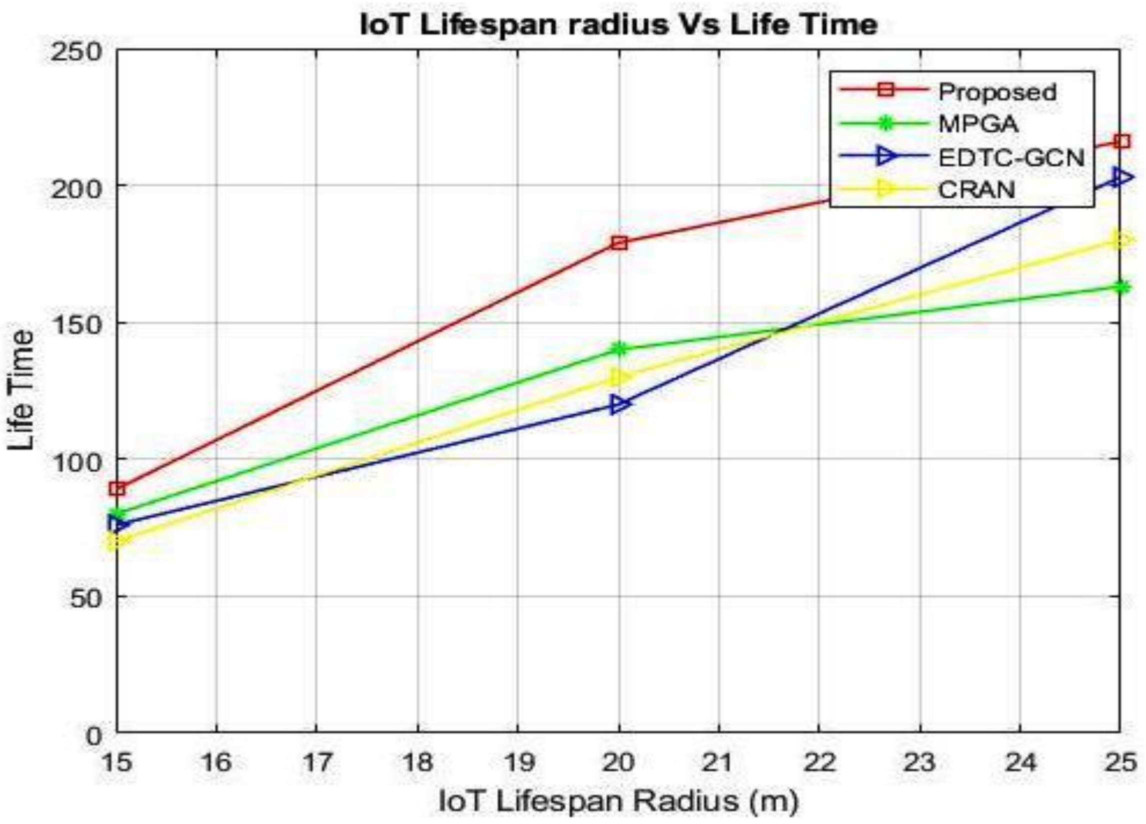

Figure 5.16 the IoT Lifespan radius Performance vs Life Time

The performance of IoT Lifespan radius vs. Life Time is displayed in Figure 5.16.

The suggested MOP-hyb-MFRS-IoT-5GN technique offers, at IoT Lifespan radius 15, a Life Time that is 10.11%, 14.61%, and 21.35% greater than those of the current methods, MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN-IoT-5GN, respectively.

The lifetime of the suggested MOP-hyb-MFRS-IoT-5GN technique is 21.79%, 32.96%, and 27.37% greater at IoT Lifespan radius 20 than the lifetimes of the MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN-IoT-5GN current methods, respectively.

The lifetime of the suggested MOP-hyb-MFRS-IoT-5GN technique is 24.54%, 6.02%, and 16.67% greater at IoT Lifespan radius 25 than the lifetimes of the MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN-IoT-5GN current methods, respectively.

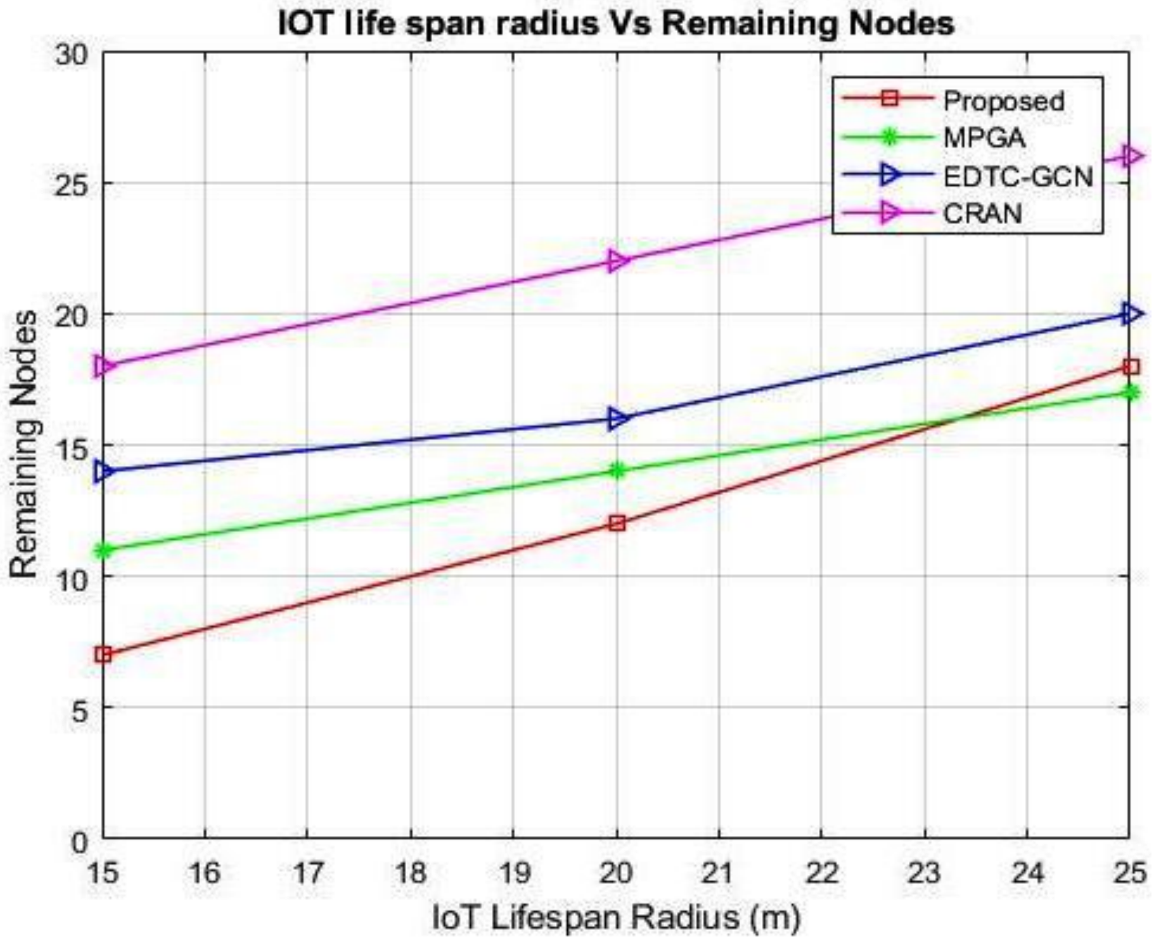

Figure 5.17 IoT Lifespan Radius Performances against Remaining Nodes

Figure 5.17 compares the IoT Lifespan radius performance to the other nodes.

The suggested MOP-hyb-MFRS-IoT-5GN technique offers 36.36%, 50.01%, and 61.11% higher remaining nodes at IoT Lifespan radius 15 compared to the current methods like MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN-IoT-5GN, respectively.

When compared to current techniques like MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN-IoT-5GN, the remaining nodes of the suggested MOP-hyb-MFRS-IoT-5GN method give 14.29%, 25.01%, and 45.45% higher remaining nodes, respectively, at IoT Lifespan radius 20.

When compared to current techniques like MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN-IoT-5GN, the remaining nodes of the proposed MOP-hyb-MFRS-IoT-5GN method give 5.26%, 10.01%, and 30.77% higher remaining nodes, respectively, at IoT Lifespan radius 25.

Scenario3 Node 200									
IOT lifespan radius Vs Computation Time					IOT lifespan radius Vs Energy Efficiency				
Life time Radius	proposed	MPGA	EDTC_GCN	CRAN	Life time Radius	proposed	MPGA	EDTC_GCN	CRAN
15	0.68	0.88	0.85	0.801	15	0.72	0.6	0.49	0.401
20	0.653	0.809	0.876	0.737	20	3.009	1.878	1.733	2.131
25	0.591	0.845	0.913	0.751	25	4.460	3.034	2.063	1.671
IOT lifespan radius Vs LifeTime					IOT lifespan radius Vs Remaining Nodes				
Life time Radius	proposed	MPGA	EDTC_GCN	CRAN	Life time Radius	proposed	MPGA	EDTC_GCN	CRAN
15	89	80	76	70	15	7	11	14	18
20	179	140	120	130	20	12	14	16	22
25	216	163	203	180	25	18	17	20	26

Table 5.4: comparison results of proposed with Different algorithms value for Node 200

The Hybridized Mayfly and Rat Swarm Algorithm exhibits promising scalability, as evidenced by laboratory experiments that involved up to 200 nodes. The algorithm's efficiency and effectiveness in managing a larger number of nodes suggest its potential scalability in scenarios with high and very high node counts. This scalability is facilitated by the incorporation of parallelization techniques, allowing the distribution of computational tasks among nodes and ensuring sustained performance. The algorithm's communication protocols are optimized to minimize overhead and enable seamless collaboration among nodes, contributing to its scalability. Additionally, the algorithm employs efficient load balancing mechanisms, preventing resource imbalances and further supporting its scalability. These positive outcomes in laboratory settings indicate the algorithm's potential to scale for real-world Internet of Things networks with a substantial number of nodes.

5.10 Limitations and Challenges

Although the Multi-Objective Programming Hybridised Mayfly and Rat Swarm IoT-5GN Algorithm has potential in addressing many goals, it is important to take into account potential constraints and problems in order to approach the job from a more balanced standpoint. Here are some important topics to talk about:

a) Algorithm intricacy:

A degree of complexity in terms of optimising and fine-tuning parameters is introduced by the hybridization of the Mayfly and Rat Swarm algorithms. During the design process, it may be difficult to strike the ideal balance between the two algorithms to guarantee efficient convergence and synergy.

b) Scalability:

It is important to carefully analyse how well the algorithm performs on large-scale IoT networks. It becomes increasingly important to provide scalability without sacrificing efficiency as the number of devices and nodes rises. For realistic implementations, scalability-related concerns must be resolved.

c) Flexibility in Changing Circumstances:

IoT ecosystems are dynamic, with requirements and situations that change over time. One major problem is to guarantee that the hybridised algorithm continues to be flexible to changes in the network, such as node additions or deletions, energy level fluctuations, or changes in coverage requirements.

d) Resource constraints and energy efficiency:

IoT gadgets frequently use little energy to function. A crucial difficulty is striking a balance between the optimisation objectives and the energy limitations of the network's components. In order to satisfy coverage and redundancy targets, the algorithm must be designed to encourage energy-efficient operations.

e) Real-world Approval:

It is necessary to test the algorithm's efficacy in a variety of real-world situations. While simulations can offer valuable insights, it is important to thoroughly address real implementation issues, such as those related to hardware limits, communication delays, and environmental conditions.

f) Trade-offs between the various goals:

In multi-objective optimisation, trade-offs between competing objectives are necessary. It's crucial to talk about how the algorithm responds to scenarios in which accomplishing one goal could negatively affect another. In multi-objective optimisation, finding a balance that satisfies particular application needs can be difficult.

g) System Sturdiness:

One factor to take into account is how resilient the hybridised algorithm is to noise, uncertainty, and unforeseen events in Internet of Things environments. The algorithm's practical usability depends on its capacity to remain stable and efficient under a range of scenarios.

h) Human-in-the-Loop Considerations:

Human interaction may be required in Internet of Things applications. It is crucial to talk about how the algorithm takes into account human preferences or decision-making. In some situations, finding a balance between human control and automatic optimisation may be difficult.

i) Implications for Privacy and Security:

Concerns about security and privacy arise when optimisation algorithms are used in Internet of Things networks. For ethical and safe deployments, it is essential to address any vulnerability and make sure the algorithm complies with privacy legislation and standards.

j) Overhead in Communication:

The communication overhead generated by the algorithm's decision-making process should be considered, especially in resource-constrained IoT networks. Minimizing unnecessary communication while maintaining coordination among devices is a delicate balance.

A comprehensive discussion on these limitations and challenges will provide a more holistic view of the algorithm's applicability, guide future research directions, and contribute to the ongoing improvement of IoT-5GN algorithms.

5.11. CONCLUSION

The issue of huge nodes will be encountered by the Internet of Things (IoT) coverage problem as 5G networks gain popularity and traction. The IoT coverage and node redundancy in IoT with huge nodes are optimized in this chapter utilizing a parallel implementation of the Hybridized Mayfly and Rat Swarm Optimizer method using Hadoop, which automatically increases the IoT's lifespan. To reduce the problem scale, parallel operation first divides the IoT coverage difficulty caused by large nodes into several smaller problems, which are then solved using parallel Hadoop. Here, the mayfly mating and flying behavior are used to optimize the coverage problem. The pursuing and attacking habits of rats are used to optimize the redundancy problem. Next, choose the non-critical nodes wisely from the crucial nodes. Finally, parallel operation effectively addresses the IoT's coverage issue with huge nodes by extending the IoT's lifecycle. The NS-2 tool is used to simulate the suggested technique. Analysis is conducted using performance indicators. such as computation time, energy efficiency, lifespan, and remaining nodes. In comparison to other methods, such as the parallel genetic algorithm to extend the lifespan of the internet of things on 5G networks (MPGA-IoT-5GN) and the energy-efficient topology control algorithm with graph convolutional network to increase the internet of things' longevity on 5G net, the proposed MOP-Hyb-MFRS-IoT-5GN method achieves lower computation times a higher lifetime.

CHAPTER -6

CONCLUSION AND FUTURE WORK

CHAPTER -6

CONCLUSION AND FUTURE SCOPE

6.1 INTRODUCTION

The development of human communication has always occurred. Communication systems have always needed to be continuously improved and refined due to the always evolving nature of technology. Communication standards have entered an entirely new era thanks to the Internet. Globally interconnecting people with gadgets and gadgets with other gadgets is a component of contemporary communication. It is necessary to automate society with the use of sensors, and the Internet of Things can help with this by employing its transmitting data network infrastructure.

As 5G networks evolve and gain popularity, the Internet of Things (IoT) connectivity issue will face the massive-node challenge. Among all IoT technologies, a hybridised Mayfly and Rat Swarm Optimizer method performed in parallel using Hadoop is suggested for improving IoT range and network reliability in IoT with large nodes, which automatically lengthens the life of IoT. It receives a lot of requests from academics and industrialists because it gives wings to the automate globe, which is really full of sensors, and it fits well for data transfer in a smart world. Because of their high demands, unique qualities, and broad range of applications in a real-time setting, the Mayfly and Rat Swarm Optimizer algorithms were chosen for our thesis study.

6.2 THE DRAWBACKS AND DIFFICULTIES OF THE MULTI-OBJECTIVE PROGRAMMING HYBRIDISED MAYFLY AND RAT SWARM IOT-5GN ALGORITHM:

a) Tuning Algorithm Parameters:

Adjusting the parameters of the Mayfly and Rat Swarm components is one of the major issues. Understanding how these algorithms work together in detail is necessary to get optimal performance, and figuring out the best mix may take a lot of trial and error.

b) IoT Networks' Dynamic Nature:

IoT settings are dynamic by nature, as devices join and exit the network and their statuses fluctuate on a regular basis. One of the difficult aspects is modifying the hybrid algorithm to handle such dynamic settings while maintaining its effectiveness in real-time.

c) The intricacy of the target functions:

Several competing objectives must be optimised in multi-objective programming. These goals become complex when they are detailed and interconnected. It is difficult to strike a balance between goals for longevity, energy efficiency, redundancy, and coverage while taking into account their complex interrelationships.

d) Reliability Problems:

There are difficulties with scaling the algorithm to support a high number of devices and nodes in vast IoT networks. As the network grows, the algorithm's efficacy and efficiency ought to be preserved without leading to a noticeably higher level of computing complexity.

e) Constrained Resource Situations:

IoT devices frequently have less processing power. One major problem is making sure the algorithm still works in contexts with limited resources, where devices could have lower processing and memory capacities.

f) Managing Diverseness:

IoT networks are made up of a variety of devices with different features and capacities. The algorithm needs to be resilient enough to manage the variety of devices, taking into account variations in communication ranges, computational power, and energy storage.

g) Implementation Challenges in the Real World:

It is not always easy to translate theoretical advances in algorithmic theory into useful real-world applications. The effective implementation of the hybrid algorithm may be impacted by interoperability problems, communication protocol concerns, and hardware limitations.

h) Energy-saving Interaction:

It is crucial to optimise device communication patterns for maximum efficiency. It is important to achieve a delicate balance between energy conservation and effective coordination, therefore the algorithm should minimise needless communication.

i) Human Communication and Personal Choices:

Knowing how the algorithm takes into account human choices and preferences is important in situations where human intervention is required. In some application situations, striking a balance between human control and automated decision-making may be difficult.

j) Privacy and Security Considerations:

The algorithm should address security concerns associated with data transmission and decision-making processes. Ensuring data privacy and protection against potential attacks is imperative for the ethical deployment of IoT algorithms.

k) Adjusting to Shifts in the Environment:

The programme must adjust to changes in the surrounding environment, including interference, weather, and network conditions. Designing mechanisms for the algorithm to dynamically respond to these changes is a challenge.

l) Multi-Objective Trade-offs:

Achieving trade-offs between conflicting objectives, such as coverage and energy efficiency, requires careful consideration. Determining the optimal compromise in situations where objectives compete is a complex optimization problem.

m) Validation in Diverse Scenarios:

Comprehensive validation across diverse scenarios is essential. The algorithm's robustness in various environments, including urban, rural, and industrial settings, should be demonstrated to ensure its versatility.

n) Interpretability and Explainability:

Understanding how the algorithm makes decisions is crucial, especially in applications where interpretability and Explainability are necessary. Ensuring that the algorithm's decisions are transparent and interpretable is a challenging aspect.

o) Regulatory Compliance:

The algorithm should adhere to regulatory frameworks and standards applicable to IoT technologies. Ensuring compliance with data protection laws and ethical guidelines is crucial for responsible deployment.

p) Continuous Adaptation:

IoT networks evolve over time, and the algorithm should be capable of continuous adaptation to new devices, technologies, and standards. Maintaining relevancy and effectiveness over the long term poses a challenge.

Addressing these detailed challenges requires a multidisciplinary approach, combining expertise in algorithm design, IoT systems, data science, and domain-specific knowledge. Continuous research and refinement are essential to overcome these challenges and enhance the applicability of the Multi-Objective Programming Hybridized Mayfly and Rat Swarm IoT-5GN Algorithm in diverse IoT scenarios.

6.3 CONCLUSION

Wireless sensor networks (WSNs) are primarily data-driven networks that have been used to enhance the Internet of Things (IoT) in the areas of data bandwidth, energy consumption, and identity. Enhancing the information longevity of WSN has an impact on IoT performance. Due to the extreme resource constraints of sensor nodes, achieving data reliability in WSN applications utilised in extreme conditions is difficult (SNs). Because of the low cost of WSN infrastructure, a number of shared storage systems have been considered with the objective of achieving information viability rather than connectivity. With the rise of the Internet of Things (IoT), many battery-powered sensors are being used in a variety of applications to collect, process, and analyse useful data. Sensors are frequently grouped into different clusters in these applications to increase overall adaptability and improved data grouping. Clustering based on node energy distribution can save resources and extend network lifespan. For our thesis work, we propose a parallelly implemented Hybridized Mayfly and Rat Swarm Optimizer algorithm using Hadoop for optimising IoT coverage and node redundancy in IoT with massive nodes, which automatically extends IoT lifespan. Initially, parallel operation divides the IoT coverage problem using huge nodes into multiple smaller issues to reduce the issue scale, which is then solved using parallel Hadoop. The scope issue is optimised here by observing mayfly flight and mating behaviour. The chasing and attacking behaviours of rats are used to optimise the redundancy problem. Then, from the critical nodes, optimally select the non-critical nodes. At last, parallel operation successfully fixes the IoT coverage issue through massive nodes by spreading false the IoT lifespan. The NS2 tool is used to simulate the proposed method. Computation Time, Energy Efficiency, Longevity, Long life, and Remaining Nodes are performance metrics that are examined.

This chapter contains a summary of the proposed Mayfly and Rat Swarm Optimizer algorithms and as well as the results of this thesis work. Furthermore, future research using the findings has been discussed. The first chapter is dedicated to introducing the thesis. The second chapter contains literature reviews on evolutionary algorithms that aid in extending the life of IoT devices and new technology that has been used to enhance the metrics of IoT applications. The following two chapters focus with the parallel implementation of two algorithms, Rat Swarm and Mayfly, which were used in the proposed work based on their behavior. The following chapter discusses the fundamental requirements and concepts underlying all research work, as well as simulation tools and proposed algorithms. A thorough review of the literature, including journals and various scholarly articles, directed me through the entire research process included journals and various scholarly articles, directed me through the entire process of research. Chapter 6 is about the real-time implementation of a parallelly implemented hybridised mayfly and rat swarm algorithm using Hadoop, in which the life time of Iot Connectivity is verified and the node coverage is tested.

As stated in the abstract, the Internet of Things (IoT) coverage problem will collide with the issue of huge nodes as 5G networks spread and become more widely used. The IoT coverage and node redundancy in IoT with huge nodes are optimised in this paper using a hybridised Mayfly and Rat Swarm Optimizer method done in parallel using Hadoop, which automatically increases the IoT's lifespan. In order to reduce the problem scale, parallel operation first divides the IoT coverage difficulty caused by large nodes into several smaller problems, which are then solved using parallel Hadoop. The flight and mating behaviour of mayflies are used to optimise the coverage problem in this case. Rats' hunting and fighting habits hunting and fighting habits of rats are used to optimize the redundancy problem. Next, choose the non-critical nodes wisely from the network nodes. Finally, parallel operation successfully solves the IoT's coverage problem with massive nodes by purposefully prolonging the IoT lifespan. The NS2 tool is used to simulate the proposed technique. Analysis is done on performance measures such as computation time, energy efficiency, lifespan, and remaining nodes. Comparing the suggested MOP-Hyb-MFRS-IoT-5GN technique to current approaches such as parallel genetic algorithm to spread the lifespan of internet of things on 5G networks (MPGA-IoT-5GN) and energy-efficient topology control algorithm with graph convolutional network to spread the lifespan of internet of things on 5G net, the proposed method achieves shorter computation times of 98.38%, 92.34%, and 97.45%, higher lifetime of 89.34%, 83 (CRAN- IoT-5GN).

6.4 FUTURE SCOPE

1. Implementation of security heterogeneity in the network's nodes in the future.
2. In the future, a number of other performance indicators, such as latency, node mobility, connection lifetime, etc., can be taken into account to further optimise energy utilisation.
3. Future research can examine energy optimization for each cluster in an IoT network, and PSO can be paired with an existing method to address large-scale routing issues with hybrid sensor networks.

4. The proposed methodology can be used to resolve security vulnerabilities that have been addressed by other researchers.
5. In the future, enhance, and employ more algorithms, particularly evolutionary algorithms, to handle scheduling problems.

In order to satisfy users, a broaden the scheduling problem by concentrating on maximising a variety of other objectives, including time, utility costs, virtual servers, and energy use. For increased practicality, the restrictions of a price, deadline, and resource limitations can be included.

The potential applications of concurrently implemented hybrid Mayfly and Rat Swarm algorithms for redundancy and coverage programming models in 5G networks for the Internet of Things (IoT) are exciting and present opportunities for several breakthroughs. Here are a few possible avenues for future research:

Scalability in Massive IoT Deployments: The scalability of algorithms becomes crucial as IoT deployments continue to rise, particularly in the setting of 5G networks. Subsequent investigations may concentrate on augmenting the scalability of hybrid algorithms to effectively manage vast quantities of IoT devices.

Dynamic Adaptability to Network Changes: Variable network loads and device mobility are two examples of the dynamic elements that 5G networks bring. Subsequent investigations could focus on how the hybrid algorithms can adjust dynamically to modifications in the network environment, guaranteeing optimal redundancy and coverage in ever-changing circumstances.

Energy-Efficient Implementations: Algorithm optimisation for low energy consumption is still a major challenge, and energy efficiency is a critical component for Internet of Things devices. Subsequent research endeavours could investigate methods to enhance the energy efficiency of the hybrid algorithms, guaranteeing extended equipment lifespans and diminished ecological consequences.

Integration with Edge Computing: IoT architectures are starting to incorporate Edge computing. Subsequent studies could investigate how hybrid algorithms can be integrated with edge computing paradigms to facilitate decentralised decision-making, lower latency, and enhance overall system responsiveness.

Security and Privacy Considerations: In Internet of Things applications, security and privacy are critical. Subsequent investigations may focus on augmenting the security characteristics of the hybrid algorithms, tackling matters like confidential data, safe communication, and defense against online attacks.

Integration of Machine Learning: Adaptive learning can be achieved by integrating machine learning methods into hybrid algorithms. Future research may examine how machine learning models might improve decision-making, particularly in IoT contexts that are dynamic and always changing.

Optimisation for the Restrictions of Edge Devices: A large number of edge IoT devices have constrained computational power. Subsequent investigations may concentrate on enhancing the hybrid algorithms to conform to the limitations of edge devices, guaranteeing effective functioning on platforms with limited resources.

Real-world Applications and Case Studies: Information about the efficacy of the hybrid algorithms can be gleaned from practical applications and case studies in a range of IoT applications. Subsequent investigations could entail implementing these algorithms in practical settings, such smart cities, healthcare, or industrial IoT, and assessing their efficacy in realistic circumstances.

Efforts to Standardize: Creating guidelines for the use of hybrid algorithms in 5G-enabled Internet of Things environments can help ensure interoperability and broad adoption. Working with standardisation organizations to create recommendations for applying and deploying these algorithms may be a part of future study.

Improved Hadoop Integration: In order to provide effective data processing, storage, and analytics for extensive IoT deployments, future research can investigate ways to improve Hadoop's integration with IoT algorithms.

The future potential is in developing these algorithms to meet the changing demands and obstacles of IoT ecosystems provided by 5G, which will promote innovation in connection, intelligence, and dependability.

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Appendix 1

List of Abbreviations

Acronyms	Meaning
LTE	Long-Term Evolution
QoS	Quality of service
LPWA	Low Power Wide Area
LoRa	Long Range
Wi-Fi	Wireless Fidelity
NB-IoT	Narrowband-Internet of Things
NR	New Radio
eMBB	enhanced Mobile Broadband
eMTC	enhanced machine-type communication
URLLC	Ultra-Reliable Low Latency Communications
D2D	Devices to Devices
D2E	Devices and Everything
M2M	Machines to Machines
IoV	Internet of Vehicles
IoT	Internet of Things
PSME	Price, Space, Mass, and Energy
CDMA	Code Division Multiple Access
UMTS	Universal Mobile Telecommunications System
IMT-2000	International Mobile Telecommunications-2000
BDMA	Beam Division Multiple Access
FBMC	Filter Bank Multi-Carrier
MIMO	Multi input Multi Output
AI	Artificial Intelligence
RFID	Radio Frequency Identification
UID	Unique Identifier
WLANs	Wireless Local Area Network system
WSNs	Wireless sensor networks
MANET	Mobile Ad Hoc networks
GPS	Global Position System

MEMS	Micro-Electromechanical Systems
TDMA	Time Domain Multiple Accesses
EDTC	Energy Efficient Topology Control
SI	Swarm intelligence
CH	Cluster Head
WOA	Whale Optimization Algorithm
SAP	Simulated Annealing Module Placement
UAV	Unmanned aerial vehicles
EENP	Energy Efficient Node Placement Algorithm
MTC	Machine-type communication
WAIoT	Wireless Ad-hoc IoT
GCN	Graph Convolutional Network
ABC	Artificial Bee Colony Algorithm
CLPSO	Comprehensive Learning Particle Swarm Optimizer
LEACH	Low Energy Adaptive Clustering Hierarchy
IHS	Improved Harmony Search
UASNs	underwater acoustic sensor networks'
MADA-WOA	Maximum Area Detection Algorithm-Whale Optimization Algorithm
FA	Firefly Algorithm
HFAPSO	Hybrid Technique of the Firefly Algorithm with Particle Swarm Optimization
FLMFLA	Fuzzy Logic and Meta-heuristic Firefly Algorithm based Routing Scheme
NFL	No Free Lunch
CRAN	cloud radio access network
Hyb-MFRS	Hybridized Mayfly And Rat Swarm
NS-2	Network Simulator-2
OTcl	Object-oriented Tool Command Language
FNS	Fast Non Sorting

List of Publications

SCI Paper

1. B Ravi Chandra, Krishan Kumar, Ajay Roy, Shamimul Qamar, Mohammed Inamur Rahman, Abdulelah G.F. Saif, "Genetic Algorithm For Higher Ensured Lifespan Of Internet Of Things In 5G Network", in SCI journal of Computers and Electrical Engineering, Vol. 106, pp-1-18, Year 2023 ISSN 0045-7906.
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