PERFORMANCE ANALYSIS OF COGNITIVE RADIO BASED IOMT FOR SECURE TRANSMISSIONS WITH WIRELESS ENERGY HARVESTING

Thesis Submitted for the Award of the Degree of

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in

Electronics and communication Engineering

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DECLARATION

I, hereby declared that the presented work in the thesis entitled "**Performance Analysis of Cognitive Radio based IoMT for Secure transmissions with Wireless Energy Harvesting**" in fulfilment of degree of **Doctor of Philosophy (Ph. D.)** is outcome of research work carried out by me under the supervision of **Dr. Jai Sukh Paul Singh** working as Assistant **Professor**, in the **Electronics and Communications Department** of 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 "**Performance Analysis of Cognitive Radio based IoMT for Secure transmissions with Wireless Energy Harvesting**" submitted in fulfillment of the requirement for the award of degree of **Doctor of Philosophy (Ph.D.)** in the Electronics and Communications Engineering Department , is a research work carried out by Mr. B. Naresh Kumar, 41900553, is bonafide record of his/her 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 the modern era, the ubiquitous presence of IoT devices spans across all industries, facilitating remote data gathering and offering a myriad of services to users. Particularly within healthcare, the advent of IoMT (Internet of Medical Things) devices has emerged, dedicated to gathering and storing patient health data in databases. This information undergoes meticulous monitoring by medical professionals, who then provide personalized recommendations aimed at enhancing patient well-being. The exponential proliferation of IoT devices within networks has led to a strain on available spectrum resources, resulting in challenges in delivering uninterrupted services across the ISM band. Addressing the issue of spectrum scarcity involves leveraging cognitive radio technology, which allows for the dynamic utilization of spectral bands opportunistically. Additionally, battery-operated IoT devices contend with energy limitations due to constant data transmission and monitoring, thereby reducing network longevity. To mitigate these constraints, an Energy Harvesting model is proposed to prolong the network's lifespan. Given the dynamic and open nature of the network environment, there is a potential for malicious behaviour among network nodes, significantly impacting network performance. To tackle security concerns, a trust-aware network model is introduced, incorporating trust value assignments to neighbouring nodes. The presence of nodes within the network also introduces the risk of disrupting communication dynamics if the ongoing trustworthiness of participating nodes is not rigorously upheld to ensure network security. The proposed model is developed and simulated for performance evaluation using MATLAB.

The escalating demand for radio spectrum underscores the absolutely necessity for the development of more efficient technologies to exploit and manage this resource. Cognitive radio technology, with its inherent networking capabilities, not only explores available white spectrum resources across diverse locations and timeframes but also facilitates optimal utilization of currently assigned spectrum resources. Consequently, there has been substantial progress in research on cognitive radio and its networking technologies, aimed at enhancing flexibility in spectrum utilization and management. This study presents an innovative cognitive radio routing framework tailored for efficient transmission of medical data within the Internet of Things (IoT). The framework introduces a pioneering hybrid optimization algorithm, SR-CHGWO (Spreading Rate based Corona Virus Herding Grey Wolf Optimization), specifically designed for optimal selection of cluster heads. This algorithm formulates multi-objective functions, accommodating various network constraints to enhance performance. Inspired by the hybrid nature of metaheuristic algorithms, SR-CHGWO leverages the spreading rate of network nodes in the given dimension. Based on this spreading rate, it selects one of the two optimization algorithms to address premature convergence issues commonly encountered in conventional optimization methods. To evaluate effectiveness, a comprehensive comparative analysis is conducted against conventional optimization algorithms, such as PSO, JA, GWO, and CHIO, focusing on network throughput, outage probability, delay, and energy consumption. Findings demonstrate notable improvements of 42.50%, 27.18%, 33.16%, and 20.30%, respectively, compared to existing algorithms. Furthermore, simulation results underscore the algorithm's superior computational complexity relative to traditional optimization approaches.

Moreover, an Energy Harvesting (EH) model based on Cognitive Radio is proposed, integrating a Hybrid Base Station (HBS) that captures energy through one antenna while concurrently transmitting data via another. In this simulation, a piecewise linear energy harvesting model is adopted. A routing strategy emphasizing energy efficiency is formulated, leveraging multi-objective optimization principles to select the optimal cluster head for data transmission across the EH-CRN (Energy Harvesting Cognitive Radio Network). This strategy employs the HCSEHO (Hybrid Cuckoo Search Elephant Herding Optimization) algorithm, which aims to maximize the Energy Harvesting rate from the surrounding network. The network's performance is exhaustively assessed, with experimental findings highlighting the superiority of the proposed optimization approach over conventional methods. Specifically, the HCSEHO algorithm surpasses PSO, ROA, CSO, and EHO by margins of 0.48%, 79.29%, 10.90%, and 44.92%, respectively, in terms of Harvested Energy across 100 nodes.

Ultimately, the study expands its purview to address the security challenges inherent in the evolved EH CR network. These concerns primarily centre around the potential presence of eavesdropping nodes, which have the capability to severely compromise the network's Quality of Service (QoS) metrics. To mitigate such risks, a meticulously crafted Trust-aware model is introduced. Within this model, the trustworthiness of neighbouring nodes is assessed based on their direct and indirect trust values, ensuring the reliability of the forwarding nodes. Only nodes with trust values meeting the set threshold level are permitted to participate in communication. The developed SA-LBOA (Self-Adaptive Ladybug Beetle Optimization Algorithm) selects the cluster head based on the optimal trusted node and other network parameters using multi-objective optimization techniques. The performance of the proposed optimization algorithm is compared against conventional algorithms like DHOA, SSO, and HLBO in terms of network QoS parameters such as Outage Probability, Hop Count, Throughput, and Trust value. Simulation results demonstrate the superior performance of the proposed algorithms compared to conventional ones.

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CHAPTER 1
INTRODUCTION

1.1 Cognitive Radio Sensor Networks

Wireless Sensor Networks (WSNs) are made up of several small, low-power devices known as nodes. They have a variety of uses in a variety of industries, from the military to the medical field. [1]. IoT has been used by researchers in healthcare applications recently to continually monitor patient temperature, heart rate, blood pressure, and sugar levels. The collected sensor data is often used for disease diagnosis and clinical care[2].Transmitting this large amount of clinical data over the wireless medium is a challenging task as the available spectrum is limited. These days, WSNs function in the ISM band (Industrial, Scientific, Medical), which is also used by other communication systems. Different technologies operating in the same ISM band have been shown in recent research to have an adverse effect on WSN performance as a whole. Data traffic is predicted to reach 4394 EB (Exa Bytes) by 2030 due to the rapidly growing number of wireless devices that are linked and the rising number of applications (Source: ITU).

The use of WSNs is expected to increase dramatically, which will result in overcrowding in the radio frequency (RF) spectrum band. Researchers are searching for new spectral bands or alternate methods to overcome the issues associated with the crowded spectral bands. Remarkably, research found that the spectrum allotted for different uses is underused. A number of the shortcomings of traditional WSNs may be mitigated by integrating cognitive techniques into WSNs. A new network known as Cognitive Radio Sensor Networks (CRSN) is formed if cognitive techniques are included into WSN. More than 70% of the allotted radio spectrum remains inactive at certain times or places, according to a 2002 FCC analysis [3]. White spaces are the underused and unused frequency spectrum areas from a technological perspective (Webb, 2012). It may be possible to lessen spectrum shortages by making effective use of these white spaces. Cognitive Radio (CR) is a technology that enables the use of white spaces in the spectrum [4]. In a 1998 lecture at the KTH Royal Institute of Technology in Stockholm, Joseph Mitola III initially introduced the idea of cognitive radio. Mitola and Gerald Q. Maguire, Jr. then published an essay on the issue in 1999. An embedded cognitive engine found in cognitive Sensor Networks (CSN) is capable of monitoring network conditions, analyzing itself, drawing lessons from past experiences, and making decisions [5].

In order to maximize spectrum usage, a cognitive radio node (SU-Secondary User) senses its surroundings and modifies its transmission settings in accordance with the knowledge it gathers [6]. Cognitive radio scans the spectrum, finds the empty bands, and uses these accessible bands opportunistically to increase total spectrum utilization by dynamically altering its operational settings. Upon initiating communication, the Primary User (PU) requires the cognitive radio user to perform three tasks: spectrum sensing, spectrum decision, and spectrum handoff, which involves adapting the transceiver to continue active communication on the new channel after identifying potentially vacant bands. This sequence of operation outlines a typical cognitive cycle in Fig.1.1. Wireless sensor networks (WSNs), which are often thought to use fixed spectrum allocation and are defined by the communication and processing resource limitations of low-end sensor nodes, may also benefit from cognitive radio capabilities [7].

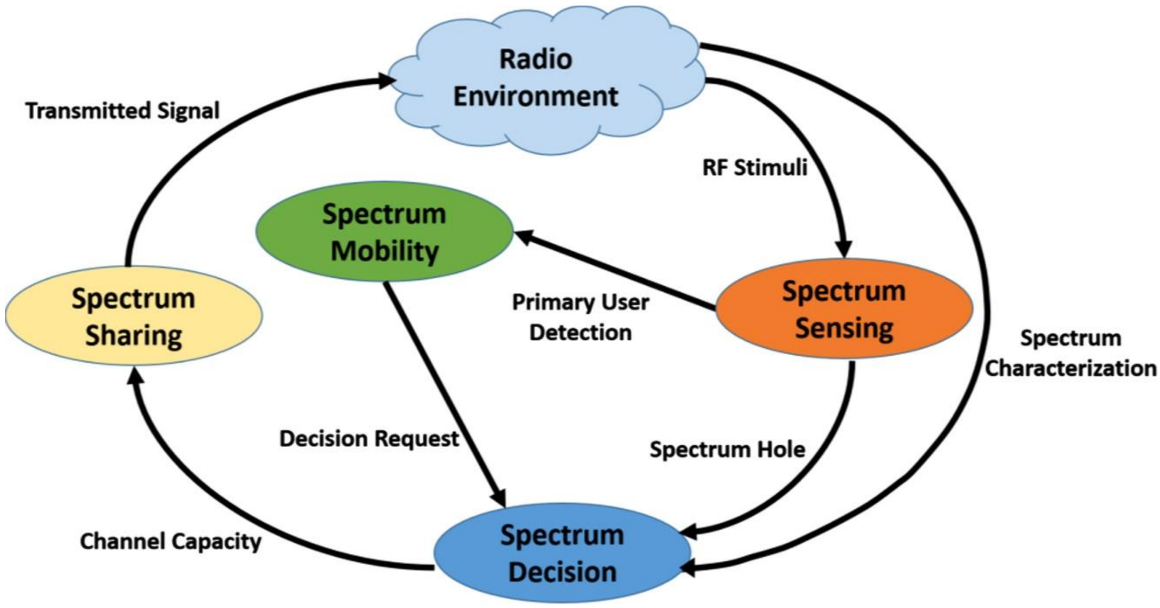


Fig.1.1 Cognitive Radio Cycle

Spectrum Sensing: In the cognitive radio network, the cognitive user will understand its radio environment and make decisions about the availability of the spectrum holes (Whi. This information will be sent to the central node or to the neighboring nodes based on the type of cognitive radio network.

Spectrum Decision: Based on the attributes of the channel, including data rate, error rate, statistics of the main user, and QoS needs of the cognitive users, a selection of available channels is chosen to allocate cognitive users to. Based on the aforementioned features, this module selects the optimal channel to be utilized by the cognitive user from those that are accessible.

Spectrum Sharing: Users share channels during communication because wireless communication is shared. The spectrum sharing module is incorporated into the functional module of spectrum management for effective channel use and equitable distribution of network resources across cognitive users. CRSNs cannot be directly subjected to the classical wireless medium access control protocols (CSMA/CA, IEEE 802.11) due to the two distinct user types (licensed and unlicensed users). Cognitive users should not take precedence over licensed users. different spectrum allocation and access procedures are implemented by the Spectrum Sharing module to prevent interferences amongst distinct cognitive user broadcasts.

Spectrum Mobility: Users are aware of the channels in a wireless network situation. However, users of the Cognitive Radio Ad-Hoc Network are unaware of the idle channel information. Channel status information is provided by the Spectrum Sensing module. Because of the actions of the primary user, a new kind of hand-off emerges. When the channel's primary user becomes active, cognitive users must stop transmitting. The secondary user either finds a new, unoccupied channel or waits for the primary user to leave the band when the primary user becomes active. For dependable end-to-end communication, cognitive users need to alert the source node's application to changes in the network so that it may adjust and slow down transmitting until a connection is established again. Handoff of the spectrum takes place: When the main user is discovered; when the cognitive user loses connection because of the movement of intermediate users engaged in communication; or when the existing spectrum band is unable to provide the necessary quality of service.

1.2 Routing techniques in CR Networks

Cognitive Radio Sensor Networks (CRSNs) combine the principles of cognitive radio and wireless sensor networks to enable intelligent spectrum access and efficient communication in dynamic and often congested radio environments. The routing protocols intended for WSN are not suitable for CR networks because of the dynamic availability of the spectral resources in the CR environment. Sensing idle bands and quickly switching between the available spectrum is a difficult challenge since Cognitive Radio Network continuously monitors the licensed band. Routing in CRSNs is a critical aspect, and various routing protocols have been proposed to address the unique challenges posed by the combination of cognitive radio and sensor network characteristics. A detailed survey on CR routing protocols is given in [8].

Some CR routing protocols include Cognitive Radio Aware Routing Protocol (CRP), Quality of Service (QoS)-Aware Routing Protocols, Cognitive Radio-based Energy-Efficient Routing (CR-EER), Spectrum-Aware Routing Protocol (SARP), Dynamic Spectrum Access (DSA)-Based Routing, Cooperative Spectrum Sensing Routing Protocols, Cross-Layered Routing Protocols, and Load-Balancing Routing Protocols. Clustering routing protocols are assumed to be efficient in terms of energy efficiency and other QoS perspectives.

Optimum cluster head selection in CRSNs is crucial for efficient operation and resource management. Cluster-based approaches are commonly used in wireless sensor networks and cognitive radio networks to organize nodes into clusters, with each cluster having a designated cluster head. The cluster head plays a central role in managing communication within its cluster, coordinating spectrum access, and facilitating efficient data transmission.

Cluster head rotation can prevent premature node depletion and enhance network resilience. Machine learning and artificial intelligence techniques can be applied to predict future node behavior and dynamically select the cluster head. Adaptive algorithms can dynamically adjust selection criteria based on real-time network conditions, ensuring that the

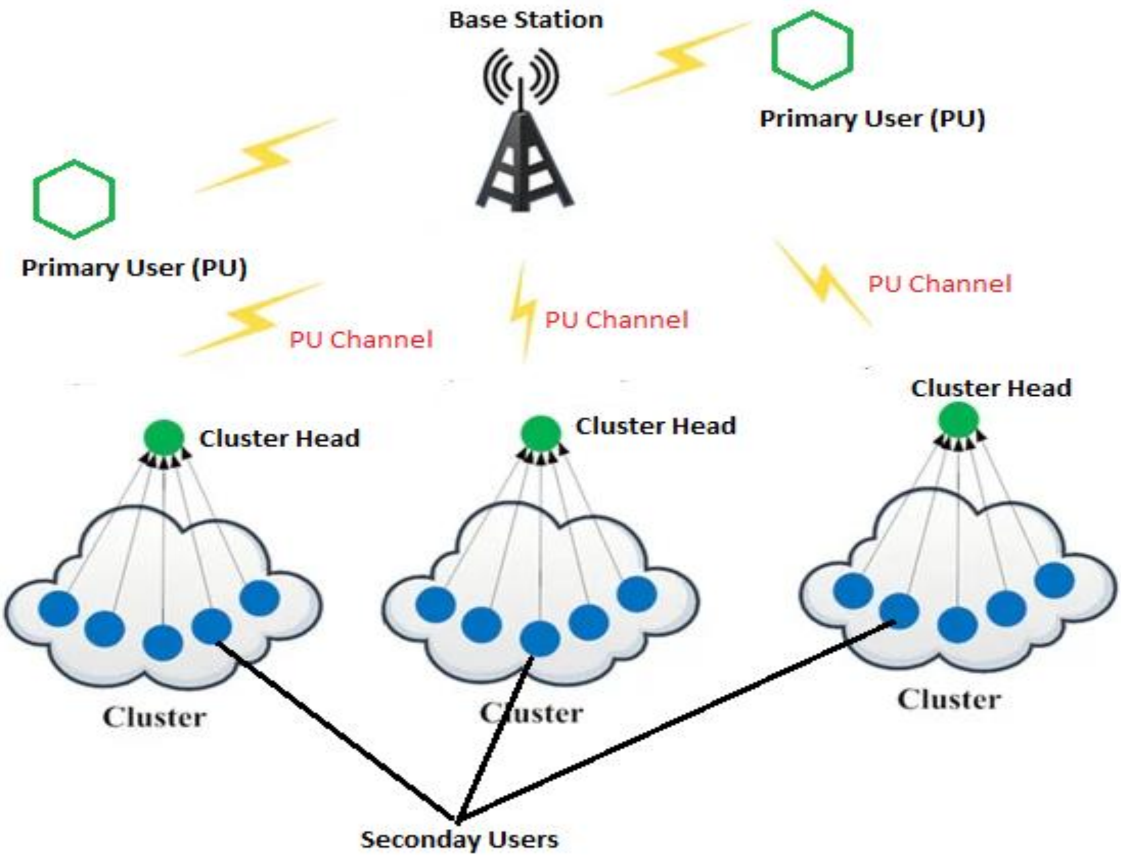


Fig.1.2 Cognitive Radio Routing using Cluster Head

cluster head selection process remains responsive to changes in the cognitive radio environment.

The process of choosing the best cluster head is difficult and involves juggling a number of variables and making adjustments for cognitive radio networks' dynamic structure. Researchers are still looking at new methods and algorithms to improve how well cluster heads are chosen in these networks.

1.3 Multi Objective Optimization Algorithms for Cluster Head Selection

Multi-objective optimization algorithms are employed when there are multiple conflicting objectives that need to be considered simultaneously in the decision-making process. In the context of cluster head selection in cognitive radio networks, where various factors such as energy efficiency, communication reliability, and spectrum utilization are important, multi-objective optimization techniques can be valuable.

Multi-objective optimization algorithms are used to solve complex problems involving multiple conflicting objectives. These algorithms are particularly useful in cognitive radio networks, where factors like energy efficiency, communication reliability, and spectrum utilization are crucial. Commonly used algorithms include NSGA-II, MOEA/D, MOPSO, NSPSO, MOGWO, RVEA, GDE3, MOABC, SPEA2, and HypE. NSGA-II uses a non-dominated sorting mechanism and elitism to efficiently evolve solutions. MOEA/D decomposes a multi-objective problem into scalar subproblems, optimizing each subproblem concurrently. MOPSO uses a population of particles to explore the solution space, while NSPSO combines PSO with non-dominated sorting to maintain diverse solutions. MOGWO uses a hierarchical structure to represent the population of wolves and aims to find Pareto-optimal solutions. RVEA uses reference vectors to guide the search process, while GDE3 employs differential evolution strategies.

When applying these algorithms to cluster head selection in cognitive radio networks, objectives such as energy efficiency, communication reliability, and spectrum utilization can be defined, and the algorithms can be tailored to find a set of solutions that represent trade-offs between these objectives. The ultimate goal is to obtain a Pareto-optimal front that provides decision-makers with a range of feasible solutions based on their preferences and requirements.

1.4 Energy Harvesting in Cognitive Radio Sensor Networks

The act of absorbing and transforming minute quantities of ambient energy from the surrounding environment into useful electrical power is called energy harvesting, often referred to as energy scavenging or power harvesting. With the use of this technology, gadgets may function or replenish their batteries independently of external power sources.

Numerous energy harvesting methods may be used to capture energy from a range of sources.

Photovoltaic cells are used in solar energy harvesting to transform sunlight into electrical energy. Kinetic energy is generated through piezoelectric devices, while electromagnetic induction converts kinetic energy into electrical energy. Thermal energy is generated through thermoelectric generators, while vibration energy is captured by vibration harvesters. Radio frequency energy is captured through RFID devices, while wind energy is generated by small wind turbines. These energy harvesting techniques are commonly used in low-power applications like wireless sensor networks and wearable devices, where traditional power sources may be impractical or unavailable.

Radio Frequency (RF) energy harvesting in Cognitive Radio (CR) networks involves capturing and converting ambient RF signals into electrical energy to power devices within the cognitive radio ecosystem. Cognitive Radio is a technology that allows devices to intelligently and dynamically access available radio frequency spectrum bands, optimizing spectrum utilization. RF energy harvesting can be beneficial in cognitive radio networks for powering low-power devices, sensors, or even enhancing the energy efficiency of cognitive radio components.

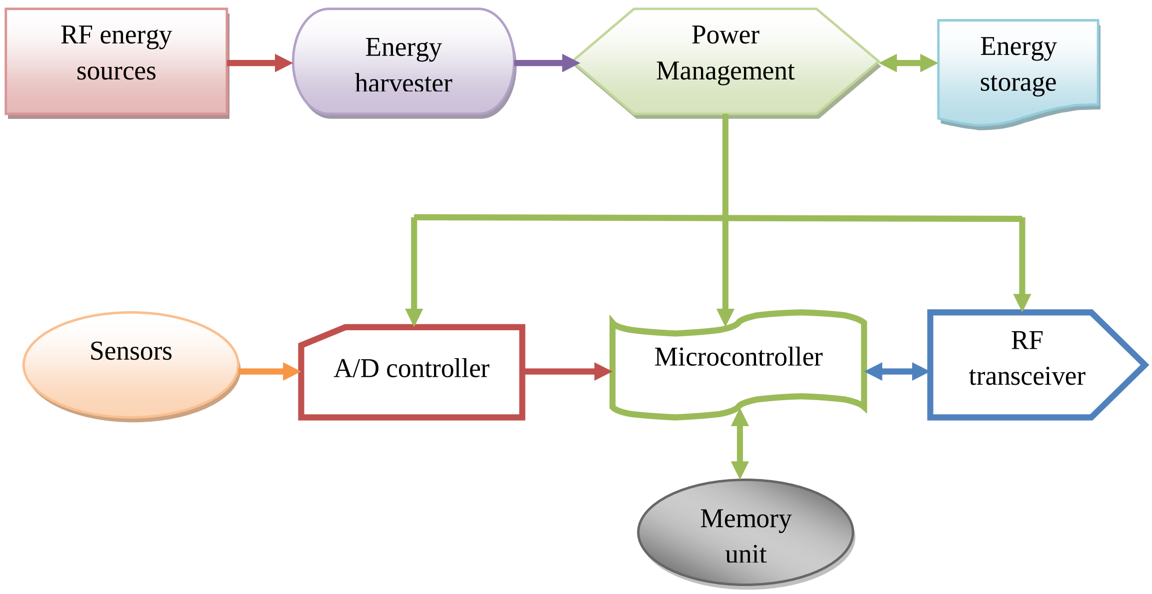


Fig.1.3 General Architecture of the Energy Harvester

The proposed present work intended to integrate cognitive radio with IoT to transmit the medical data securely over the wireless networks using energy harvesting schemes which improves the lifetime of the sensing node.

1.5 IEEE Standard used for Cognitive Radio Networks:

The IEEE 802.22 standard is used for to Cognitive Radio Sensor Networks (CRSN) deployed within the Internet of Medical Things (IoMT). It will make use of the underutilized TV spectrum, generally known as TV whitespace, to facilitate wireless communication. This adaptation makes it an ideal choice for IoT scenarios where spectrum availability might be constrained. IEEE 802.22 meticulously defines the Physical Layer (PHY) and Media Access Control (MAC) specifications used for Wireless Regional Area Networks (WRANs) operating within the TV whitespace spectrum. Here, we highlight some important radio specifications defined by this standard:

Frequency Bands: IEEE 802.22 works in the VHF and UHF bands, using TV broadcasters' "whitespace" channels that aren't being used. Most of the time, these bands are between 54 MHz and 862 MHz in the US, but they can be different in other places.

Channel Bandwidth: The standard allows for variable channel bandwidths, which are usually between 6 MHz and 8 MHz, which is the same range of frequencies used for regular TV broadcasting. Regulations and available spectrum determine the actual channel bandwidth that is used.

Modulation: IEEE 802.22 specification support different modulation schemes based on the requires data rates and the available channel conditions. Generally, OFDM and other broadband modulation techniques are suitable for dynamic and frequency selective environments.

Transmission Power: The standard specifies maximum transmission power levels allowed for IEEE 802.22 devices to minimize interference with licensed users and ensure regulatory compliance. Power control mechanisms may also be employed to adjust transmission power based on proximity to other users and environmental conditions.

Spectrum Sensing: IEEE 802.22 devices are equipped with spectrum sensing capabilities to detect the presence of primary users (e.g., TV broadcasters) and avoid interference with their transmissions. Spectrum sensing techniques may include energy detection, cyclostationary feature detection, and other methods to reliably identify vacant channels for operation.

Antenna Requirements: The standard may include recommendations or requirements regarding antenna configurations and characteristics to optimize radio performance, coverage, and interference mitigation. Antenna diversity and beamforming techniques may be employed to improve signal reliability and range.

Channel Access Mechanisms: IEEE 802.22 employs dynamic spectrum access mechanisms to enable efficient and fair utilization of available spectrum. MAC protocols govern channel access, spectrum sensing, and coordination among WRAN devices to prevent interference and ensure coexistence with primary users and other secondary networks.

These specifications provide the foundation for IEEE 802.22-compliant devices to operate in TV whitespace spectrum, offering broadband connectivity over long distances in rural and underserved areas while minimizing interference with incumbent users.

1.6 Motivation

CRSN represents a specialized form of wireless sensor networks, where nodes are equipped with cognitive radio capabilities to adaptively access and utilize available radio frequency spectrum. The selection of Cluster Heads in CRSNs is a crucial task, and various conventional routing protocols have been proposed to enhance network lifetime and energy efficiency by considering single objective constraints. However, routing large data packets over the cognitive radio network presents challenges in terms of energy efficiency, throughput, delay, and network outage probability. To address these multiple constraints, there is a need for the development of multi-objective optimization algorithms.

The proposed work aims to integrate cognitive radio with energy harvesting capability to securely transmit health information over the Medical IoT (IoMT). The goal is to increase the network's lifetime by developing multi-objective optimization algorithms. Single-objective optimization methods developed for cluster head selection in CRSNs have limitations in addressing multiple problems. They struggle to handle multiple conflicting objectives, leading to suboptimal solutions. These methods are not robust to objective function changes, making adaptability challenging in evolving problem formulations. Moreover, they face difficulties in handling constraints effectively, resulting in infeasible solutions.

Single-objective optimization methods focus on finding a single optimal solution, potentially leading to premature convergence and neglecting diverse solutions. They are highly sensitive to initial conditions, making it difficult to obtain consistent results. Additionally, these methods face challenges in handling non-smooth or discontinuous objective functions, limiting their effectiveness for problems with discontinuities. Furthermore, they encounter computational complexity for large-scale problems and exhibit limited adaptability to dynamic environments.

In contrast, multi-objective optimization methods provide a powerful framework for selecting the optimum cluster head in CRSNs. These methods balance multiple conflicting objectives simultaneously, addressing concerns such as throughput maximization, minimizing hop count, and reducing outage probability. Integrating energy harvesting and security models into the optimization process enhances the overall performance and resilience of the cognitive radio network.

1.7 Thesis Aim and Objectives

In this section, we outline the main objectives and aim of the thesis based on the identified motivations. The primary goal is to design and integrate cognitive radio with energy harvesting (EH) to securely transmit health over IoMT, ultimately enhancing the lifetime of the Cognitive Radio (CR) Network.

The major objectives of this thesis are:

- To develop a cognitive radio framework for the transmission of medical data over the network using IoMT.
- To develop an energy harvesting model to enhance the lifetime of the CRN node.
- To develop a security model for the secure transmission of medical data over the cooperative EHCRN.

The above objectives are implemented using various optimization algorithms as summarized below

- **Development of Cognitive Radio Routing Framework:** The first objective involves the creation of a cognitive radio routing framework dedicated to transmitting medical data over the network utilizing IoMT. To assess the performance of the Cognitive Radio (CR) based IoMT, a novel hybrid multi-objective optimization algorithm, named SR-CHGWO (Spreading Rate based Corona virus Herding Gray Wolf Optimization), is proposed. This algorithm aims to optimize the routing process, considering multiple objectives simultaneously.
- **Implementation of Enhanced Energy Harvesting Scheme:** The second objective aims to incorporate energy harvesting technique in CRSN to improve the network's lifespan. This involves the implementation of a hybrid optimization strategy called Hybrid CSO (Cuckoo Search Optimization) -EHO (Elephant Herding Optimization) Algorithm names as HCSEHO. The main goal is to select an optimal cluster head, facilitating effective data transmission from source to destination by minimizing interference and reducing information loss in the network.

- **Develop Trusted EH-CRSN network for Secure data Transmission:** The third objective involves the development of the SA-LBOA (Self Adaptive Ladybug Beetle Optimization Algorithm), an enhanced heuristic technique. This technique is designed to ensure trustworthy performance in the CR Network by optimally selecting the CH (Cluster Head) for efficient data transmission between source and destination nodes.

Several QoS metrics which are commonly used to measure the performance of the network are outlined below:

End-to-End Delay (Cumulative Delay): The elapsed time taken by a generated data packet to traverse from its source to the intended destination. This metric quantifies the total time it takes for data to travel through the network, measuring the delay experienced by packets in reaching their final destination.

Throughput: The quantity of successfully received data packets within a specified timeframe. Throughput measures the efficiency of data transfer by assessing the rate at which packets are successfully delivered within a given time window.

Hop Count: The number of intermediate hops a data packet traverses from its source node to the designated destination. This metric quantifies the number of intermediary nodes a packet encounters during its journey through the network, providing insight into the route complexity.

Packet Delivery Ratio: The ratio of received data packets at the destination to the total number of generated data packets at the source. Packet delivery ratio assesses the effectiveness of the routing protocol by determining the proportion of successfully delivered packets compared to those initially generated.

Network Lifetime: The operational time of the network until the occurrence of the first network partition. Network lifetime measures the duration of uninterrupted network operation, providing information on the system's resilience before the occurrence of a partition.

Energy Consumption: The total amount of energy consumed by network nodes. Energy consumption quantifies the power usage of individual nodes within the network, offering insights into the sustainability and efficiency of the overall network infrastructure.

By delineating these objectives, the thesis aims to make significant contributions to the fields of cognitive radio, energy harvesting, and secure medical data transmission over the IoMT. The proposed algorithms, CHGWO, HCSEHO, and SA-LBOA, are anticipated to play pivotal roles in achieving the stated goals, thereby advancing the state-of-the-art in CR Networks and their applications in healthcare.

1.8 Contributions of the Thesis

The major contributions of the thesis as summarized as below

IoT Devices in Healthcare: Highlighting the emergence of IoMT devices dedicated to gathering and storing patient health data, enabling personalized recommendations for enhancing patient well-being within the healthcare industry.

Addressing Spectrum Scarcity: Discussing the challenges posed by the exponential growth of IoT devices on available spectrum resources and proposing the use of cognitive radio technology to dynamically utilize spectral bands for optimal resource management.

Energy Harvesting Model: Introducing an Energy Harvesting model to prolong the lifespan of battery-operated IoT devices by addressing energy constraints through innovative approaches, such as integrating a Hybrid Base Station for simultaneous energy capture and data transmission.

Optimization Algorithms: Presenting pioneering hybrid optimization algorithms, like SR-CHGWO and HCSEHO, tailored for efficient data transmission and cluster head selection within IoT networks. These algorithms aim to improve network performance and address convergence issues common in conventional optimization methods.

Security Concerns and Trust-aware Model: Discussing security challenges in IoT networks, particularly the risk of eavesdropping nodes, and proposing a Trust-aware model that evaluates the trustworthiness of neighboring nodes to ensure reliable communication. The developed SA-LBOA algorithm selects optimal cluster heads based on trust values and network parameters to enhance security and performance.

Comparative Analysis: Conducting a comprehensive comparative analysis against conventional optimization algorithms, demonstrating significant improvements in network throughput, outage probability, delay, energy consumption, and harvested energy, thereby showcasing the superiority of the proposed algorithms.

1.9 Organization of the thesis:

Chapter 1 explores the basic concepts of EH enabled Cognitive Radio Networks and routing methods using clustering approach along with Multi objective Optimization requirements to enhance the various metrics associated with CRN. Additionally, it also elucidates the research motivation, objectives, major contributions of the thesis and organization of thesis.

The rest of the thesis is organized in the following manner:

Chapter 2 portrays the literature work of existing energy-efficient routing models in CRSN and EH-CRSN, which is represented in categorization of works. Research gaps and challenging problems are involved in stimulating the better process.

Chapter 3 presents Intelligence based Optimum Routing strategy to improve the performance of the CR network for medical data transmission using IoMT

Chapter 4 illustrates the development of Energy Harvesting model to improve the energy efficiency and thereby increasing the network lifetime.

In chapter 5 we study various security attacks associated with EH based cognitive networks and proposes a trust aware routing strategy for secure data transmission by using Multi Objective Optimization Concepts.

Finally, **Chapter 6** concludes the thesis and **Chapter 7** directs some future research topics.

CHAPTER 2
LITERATURE REVIEW

2.1 Background

The design of communication systems is a complex task that centers on the efficient utilization of two critical resources: bandwidth and power [9]. Communication system designers aim to optimize the use of these resources to meet specific requirements and ensure reliable and high-performance operation. In recent years, the rapid progress and increased potential of wireless communication technology have fueled a growing demand for spectrum resources [10]. One notable application of wireless communication is the deployment of Wireless Sensor Networks (WSNs). WSNs are composed of autonomous sensors distributed across a geographical area, collaborating to monitor physical or environmental conditions and transmitting collected data to a central location [11]. These sensor nodes, often compact and cost-effective, are equipped with various sensors to measure parameters such as temperature, humidity, light, and pressure, resembling Internet of Things (IoT) devices [12]. The nodes within a WSN are interconnected wirelessly, forming a self-configuring network with versatile deployment capabilities in applications ranging from environmental monitoring to industrial automation, healthcare, home automation, and military systems [13]. Given the diverse scenarios in which WSNs are applied, the effective use of bandwidth and power in their design is pivotal to ensuring reliability and optimal performance [12].

Cognitive Radio Sensor Networks (CRSNs) have emerged as a solution to address the significant challenges faced by traditional Wireless Sensor Networks (WSNs). WSNs encounter various limitations, including limited spectrum availability leading to congestion and interference, inefficient use of frequencies due to fixed spectrum allocation, degradation of communication reliability from interference by other devices or networks, energy constraints impacting network lifetime, unreliable communication due to environmental changes or network failures, a lack of effective mechanisms for ensuring Quality of Service (QoS) in data transmission, and suboptimal performance in dynamic environments with static routing strategies. To overcome these challenges, CRSNs integrate cognitive capabilities that facilitate dynamic spectrum access, interference mitigation, energy efficiency, reliability improvement, QoS enhancement, and adaptive routing. The incorporation of cognitive features contributes to a more resilient and efficient sensor network infrastructure.

A Cognitive Radio Sensor Network is defined as an intelligent Wireless Sensor Network capable of perceiving, learning, reasoning, and acting through a distributed system comprising sensors, actuators, computation, and communication. This definition underscores the advanced and intelligent nature of CRSNs, highlighting their ability to adapt to changing conditions and optimize performance in various environments. Moreover, the integration of cognitive radio technology allows for the exploitation of white spaces in the spectrum, enabling cognitive radio nodes to sense their environment and adjust transmission parameters [14]. This capability becomes crucial in the context of the Internet of Things (IoT), a computing paradigm that employs sensing devices, computer nodes, and communication instruments for data collection, sharing, and remote control. In healthcare applications, for instance, IoT is increasingly utilized to monitor patients' vital signs such as blood pressure, sugar levels, heartbeat, and temperature. However, the transmission of such data over the wireless medium faces' challenges due to limited spectrum availability. Cognitive Radio technology addresses this issue by dynamically adapting to the available spectrum, ensuring efficient and reliable communication in IoT applications. Sensor nodes will utilize its battery power to sense the vacant channel statistics and send the data over the network. Over a period of time the node may lose its power leading to the failure of the nodes which break the communication link in the network. To overcome this dead node condition to dead various energy efficient resource allocation strategies were proposed but still there is requirement of power efficient node deployment and maintenance. In recent days Wireless Energy Harvesting has shown tremendous growth in its technological advancements. In this research work RF energy Harvesting is embedded in to the cognitive Radio network to recharge the battery by utilizing the Harvested energy from the RF energy available in the environment leading to the improvement in the network lifetime.

2.2 Cognitive Radio Routing Algorithms and their challenges

In Cognitive Radio Sensor Networks (CRSNs), the routing mechanisms differ significantly from those in traditional Wireless Sensor Networks (WSNs). CRSNs, specifically the subset known as Cognitive Radio Wireless Sensor Networks (CR-WSNs), present a unique set of challenges and considerations that make routing more complex compared to traditional WSNs. Unlike traditional WSNs where routing decisions are primarily based on considerations such as energy efficiency, node proximity, or hop count, CRSNs introduce an additional layer of complexity. In CRSNs, routing must be intricately integrated with the process of sensing spectrum availability. Spectrum sensing is a fundamental capability in cognitive radio networks, allowing nodes to identify and adapt to available frequency bands dynamically. In the context of CR-WSNs, routing decisions need to be made not only based on traditional factors but also considering the dynamic and opportunistic nature of the available spectrum. Nodes in CRSNs must assess the spectrum availability along potential routes and select paths that optimize both communication reliability and efficient use of the available frequency spectrum.

An Energy-efficient dynamic clustering approach for IoT applications (BPNN) based on Back Propagation Neural Network was proposed by L. Manman et al. in In 2020 [15]. By using Copula theory and NN (Neural Networks) concepts, the collected information is processed based on the power requirements of the individual clusters. The optimization of overall power requirements of the clusters are carried out according to network requirements, such that efficient intra-cluster packets can be done.

Wang et al. [16], in 2020, Used optimal stopping theory concepts for developing efficient routing protocols which incorporating the network coding for secure data transmission among the trusted nodes. The proposed method/approach is also utilized for trusted channel allocations to achieve improved gain for the networks. The major improvements were found in the average delay in the network and routing cost.

In 2021, Dhiman et al. [17] introduced a reconfigurable Cross Layered Routing Protocol based on Cognitive Radio Networks (CRN), aiming to enhance the network performance and optimize the data transfer rate in the adaptable networks. They used the Spotted Hyena Optimization (SHO) Algorithm to fine-tune the machine-learning model parameters efficiently. The model generates distributors encompassing various which include load balancing, developmental path of machine learning and quarter sensing. The developed technique exhibited sensitivity to factors such as traffic, charges, and a range of other QoS metrics. Testing was conducted using classic models to showcase the residual energy, resilience, scalability, and resource strength. In 2021, A. Mukherjeee et al. [18] introduced a zestful clustering model that relies on a crossbreed optimization approach combining neural networks (NN) and the Gaussian copula method. The adoption of this strategy resulted in notable reductions in both calculation time and energy consumption.

To prolong the lifespan of Wireless Sensor Networks (WSNs), the authors in [19] used PSO algorithm for Clustering the randomly deployed nodes. Two factors, average cluster distance and life span of the gateway are taken into consideration for the formation of clusters in this approach. The cost-function method is employed to compute the fitness value of each particle, these values contribute to the overall quality of the system. Particles with a greater cost function value contribute to the efficient network establishment.

Researchers in [20] explored MIMO technology for the identification of Cluster Heads within a distributed WSN. This model employs an iterative method (in cooperative intra-cluster networks) based on the concepts of linear regression determine position of the CH in the intended cluster. The approach utilizes a distributed gradient method to accurately localize the CH and enhance the efficiency of the wireless sensor network.

In [21], the challenge of identifying the locations of Cluster Heads (CHs) in MIMO sensor networks, specifically for Intelligent Transportation System (ITS) applications, was addressed. The authors utilized a combination of Back Propagation Neural Network (BPNN) and the distributed gradient drop approach to identify CHs in MIMO sensor networks, aiming to reduce the overall estimation error. Additionally, Gopi Krishnan et al. [22] suggested a new protocol for IoT applications in Cognitive Radio Sensor Networks (CRSNs). By addressing energy and delay issues, the proposed communication protocol was evaluated against existing methods, demonstrating improved performance in terms of energy utilization and delay.

In 2020, Vimal et al. [23] introduced a pioneering heuristic algorithm titled "Multi-objective Ant Colony Optimization (MOACO)" incorporating DL network. This algorithm integrates a clustering technique to optimize data utilization and improve inter cluster data aggregation. This method aims to prolong the networks lifespan, emphasizing green communication through artificial intelligence-based modeling. Validation results indicate improvements in throughput and jamming prediction with the proposed approach.

In 2019, Ghose et al. [24] introduced ES (Early Sleep) and EDT (Early Data Transfer) routing schemes to minimize time delay and energy consumption while transmitting data packets in the network. The ES method involves Decoding and validation of addresses were taken care by ES method, leading non-destined devices to enter a sleep mode. The efficacy of these devised techniques was evaluated through simulations and theoretical analyses.

In 2018, Anamalamudi et al. [25] created an integrated control channel employing a cognitive routing protocol to establish channel routes through directional antennas in CR networks. To maintain consistent communication and maintain synchronization with other nodes, in 2017, Qureshi FF et al. [26] designed a Cognitive Radio (CR) protocol to enhance the network throughput. The developed CR protocol exhibited faster computation times and achieved higher data transmission throughputs compared to alternative protocols. Furthermore, to address the practical issues in the Internet of Things (IoT), this is extended to make it more applicable and cost-effective.

In 2019, Kumar et al. [27] introduced “Cognitive Data Transmission Method (CDTM)" designed for observing, storing, and transmitting patient clinical data. This method leverages cognitive technology to efficiently observe and transmit clinical data to the medical experts for diagnosis purpose. Additionally, a stochastic process was employed to predict the future health status of patients based on their current health scenarios. The performance evaluation of the proposed routing protocol demonstrated accurate predictions with reduced time requirements, showcasing efficient bandwidth utilization.

In 2016, Mukherjee et al. [28] tackled issues related to the Fusion Centre (FC) through HML clustering (Hierarchical Maximum Likelihood) approach for cooperative CR networks. The FC positioning problems were also addressed in theis work. Pefkianakis et al. introduced SAMER for CR Networks in [29], introducing a trade-off between short-term opportunistic sharing and long-term route stability. Additionally, Chowdhury et al. introduced the distributed routing protocol SEARCH for mobile Cognitive Radio Networks in [30], which minimizes end-to-end latency by optimizing route and channel selection. While these methods notably enhance performance metrics without disrupting primary users' transmissions, they do not consider external interference or learning aspects.

Huang et al. in [31] provide a novel routing system for a high mobility cognitive radio network that prioritizes node capacity and path stability. For ad hoc Cognitive Radio Networks, Chowdhury et al. introduced CRP in [32] to secure Primary User Receivers, provide several class routes for various networks, and enable scalable route selection. Talay et al. created the Self-Adapting Routing (SAR) algorithm in [33], which has the capacity to manage the transmission range in an adaptive manner for ad hoc cognitive networks. This method can only be applied to underlay approaches; it is not suitable for overlay or interwoven approaches.

A multipath Quality of Service (QoS) routing system based on route stability was proposed by Sarma et al. in [34]; it improves throughput and decreases latency. On the other hand, Jin et al. presented TIGHT, a unique geographically based routing scheme, in [35] that enables cognitive users to utilize Primary Channels without interfering with Primary Users. Salameh has worked on the idea of minimizing interference to guarantee simultaneous transmission of narrowband and wideband data in [36]. An efficient routing strategy for low energy usage and decreased latency was studied and developed by Ji et al. in [37].

Therefore, routing in CRSNs involves the simultaneous consideration of traditional routing metrics, such as minimizing energy consumption and maximizing data delivery reliability, along with the added complexity of spectrum-aware routing. This introduces additional challenges in terms of designing routing protocols that can adapt to the dynamic spectrum environment, efficiently utilize available frequency bands, and ensure reliable and timely communication.

In summary, the distinctive feature of routing in CRSNs, particularly CR-WSNs, is the integration of spectrum sensing into the routing process. This integration introduces additional challenges that must be addressed to optimize the performance of the network in terms of both traditional routing metrics and spectrum-aware considerations.

2.3 Energy Harvesting in Cognitive Radio Networks

RF energy harvesting techniques in CRNs contribute to the development of self-sustainable and adaptive cognitive radio systems, reducing reliance on external power sources and improving overall network efficiency. These techniques play a crucial role in extending the operational lifetime of cognitive radio devices in dynamic and resource-constrained environments. Various types of energy harvesting technologies have been developed to harness different forms of energy. Various energy harvesting methods harness different sources to generate electrical power. [38-39].

RF (Radio Frequency) energy harvesting techniques in Cognitive Radio Networks (CRNs) aim to capture and convert ambient RF signals into electrical power, enhancing the sustainability and autonomy of devices within cognitive radio systems. Here are some RF energy harvesting techniques specifically applicable to CRNs:

Channel Sensing-Based Harvesting: It utilizes the energy received during the channel sensing process, where cognitive radios detect the availability of free spectrum bands. This energy powers the cognitive radio sensor battery during the spectrum sensing phase which will increasing energy efficiency.[40]

Harvesting from Primary User Transmissions: In this method SU Captures energy from the transmissions of primary users in the spectrum. Hence it will provide supplementary power during periods of low secondary user activity.[41]

Wideband Harvesting: It exploits wideband antennas to capture energy across a broad range of frequencies simultaneously which eventually increases the chances of harvesting energy in diverse RF environments [42].

Adaptive Harvesting Algorithms: SUs employs adaptive algorithms to dynamically adjust harvesting parameters based on the availability of RF energy and Optimizes energy harvesting based on real-time changes in the RF environment.[43]

Multiple Antenna Harvesting: Uses multiple antennas to capture RF energy from different directions simultaneously. Enhances harvesting efficiency by increasing the likelihood of capturing energy from diverse sources [44].

Energy Harvesting-Aware Routing: Integrates energy harvesting information into routing decisions, considering available RF energy during route selection. Optimizes energy usage and extends network lifetime by selecting routes with higher energy availability [45].

Energy harvesting networks (EHN) represent a dynamic field, currently facing significant challenges in technical design as highlighted in recent studies [38]. In some of the latest research efforts, EH-CRN is encountering substantial demands in terms of technical design [38]. Bhowmick et al. explored non-RF strength harvesting as a viable method for collecting energy from RF signals emitted by primary users (PU) [46-49], building upon previous work [38]. While static sources like TV and radio towers emit relatively consistent power over time, dynamic RF sources such as Wi-Fi networks and cell signals exhibit varying power levels. The energy harvesting component can be configured as either a single-stage or two-stage system, with the latter acting as a backup arrangement utilized when the energy stored in the initial stage is depleted.

D. Zhang et al.2016 Proposed algorithms for handling resource distribution of CRNs for Energy Harvesting. It collects and optimizes stochastic energy collection and processes for consumption and stochastic continuum and access processes. The author used optimization from Lyapunov to break down the problem into three more easily-solved sub-problems, battery management, sampling rate control, data rate and channel assignment [50].

M. Zareei et al. 2019 A circulated power management mechanism for energy harvesting for the CR sensor network (EH-CRSN) is recommended. The key concept is to dynamically alter the transmitting ability of the nodes to retain network access based on their network status. In accordance with a variety of parameters such as the current power and the available power of the neighboring nodes each node chooses to dynamically upsurge or lessening its transmission power. In order to properly adjust the strength of the network, this dynamic power shift transforms the network's logical topology. The power control is managed by two situations: a flat and a clustered network [51].

Ahmed Sultan et.al. 2012 The secondary consumer is an energy power with a final battery. We consider a cognitive radio environment. The primary consumer functions in a time-consuming way. The secondary consumer may remain idle or perform spectrum sensing at the beginning of each slot to optimize their output. The decision is based on the secondary opinion about primary operation and the quantity of energy retained. We describe this as a decision-making process in Markov. We present the optimal strategy, compare it and evaluate the shift in throughput with different system parameters [52].

Avik Banerjee et.al.2020 proposes a time-slotted method for the energy harvesting of cognitive radio (CR). The CR consumer simultaneously performs energy harvesting and spectrum sensing (SS) via power splitting mode. On next, the CR consumer gathers energy or conveys its own data depending on the outcome of SS decisions during the transfer time slot. To optimise the residual energy under the limitations of PU reliability and the spectrum efficiency (SE) target level of the CR an optimization issue is established. The concavity of the objective function shows that the problem is solved globally. Simulations are used to find shortened form expressions of sensing time and CR transmitting capacity [53].

G. Han et.al. 2016 The author considers that there is a cognitive radio network where a primary transmitter is located primarily on the channel and, if sensed idleness, a secondary transmitter fitted with an energizer would have access at any time to the primary channel. It is assumed here that the energy arrival process and the primary channel state are a random and two-state discreet Markov process. The authors use the optimize energy harvesting and spectrum sensing under restrictions of energy causality, collision and time correlation between likelihood of sensing idle / occupied cha instead of assuming successful access to the spectrum by time slot as a strategy criterion in current literature. In accordance with our extensive computer simulations, we obtain the corresponding optimal sensing and maximum reachable throughput [54].

S. Park et.al. (2012) The optimal method selection policy was developed by putting the decision-making problem on the exact Markov Decision Process model (POMDP). Numerical results indicate that the optimal strategy established balances the achievement of the immediate production with the collection of RF energy for future use [55].

Dinh Thai Hoang et.al. (2014) The author considers a network where a secondary user accesses the channel to pass the packet or receive RF power if the channel selected is idle or employed by the main user. In order for the secondary user to boost their flow, the author proposed an optimization framework. An online learning procedure was implemented that can observe the environment and adjust the channel access behavior without knowing the model parameters beforehand. The authors evaluated the efficiency and convergence of the study algorithm in this paper. The learning algorithm can achieve the results near the optimization result [56].

In 2020, the authors [57] suggested the “Dynamic Optimization Law over CR Networks (DOL-CRNs)”. In this method by incorporating the optimization method, they harvest the energy efficiently in CR networks. This approach has enhanced the performance of the network in terms throughput, success ratio and lifespan of the network by decreasing the overall latency in the communication.

Banerjee *et al.* [58] in 2018, have utilized a RF-EH scheme that is capable of transmitting the data in switching mode for route selection and joint power allocation in CR networks. The transmission of the data between the receiver as well as the transmitter was carried out with the aid of the relays utilizing a part of the obtained energy. By utilizing the optimization, they reduced the outage probability of the network. The constraints used for this problem formulation are corporative rate of the PU and the causality of the energy. By using Dijkstra's and Bellman-Ford's algorithms optimum routing path is attained. This enhanced the lifespan of the network and reduced the power consumption rate.

2.4 Security Issues in Cognitive Radio Networks

Energy harvesting is a technology that involves gathering energy from the surrounding environment, proving to be a valuable method for ensuring a reliable supply of power. This can be integrated with Cognitive Radio (CR) systems to prolog the lifespan of CRNs and decrease implementation costs [59]. Two commonly utilized energy harvesting architectures are "Time Switching (TS) and Power Splitting (PS)" [60]. In the Power Splitting model, the received signal power is divided into two segments: one for harvesting energy from the environment and the other for processing the received signal [61]. On the other hand, the Time Switching approach divides the transmission slot into two slots, with one slot dedicated to energy harvesting from nearby RF sources and the other for data transmission [62]. The dynamic nature of CR networks makes Secondary Users (SUs) susceptible to both internal and external attacks. Additionally, due to the broadcast nature of radio propagation, confidential messages transmitted over CRNs can incur overhead through malicious eavesdroppers [63]. Therefore, alongside managing consistent transmission, securing CRN transmission against the impacts of malicious eavesdropping is a crucial objective. The growing computational power and advancements in technology underscore the equal importance of highly secure communication to protect against adversary attacks [64].

Ensuring the security of Cognitive Radio Networks (CRN) is an essential state in which the network is accessible openly and susceptible to external attacks [65]. Eavesdroppers can lead to network infiltration [56] and result in energy loss in harvesting nodes, rendering them invalid and compromising security. In traditional CRNs, significant investments are made to enhance security, establishing a tradeoff between security improvement and the reliability of energy-harvesting-dependent CRNs [66]. To bolster network security, a cooperative jamming method, coupled with artificial interference and noise, was introduced in [67]. Furthermore, [68] proposes energy harvesting methods based on appropriate relay selection to achieve an enhanced balance between the efficiency of secondary transmission and the security of primary transmission.

In [69], an underlay Cognitive Radio Network (CRN) was explored, featuring a set of primary nodes and two secondary nodes, while assessing secrecy outage efficiency. However, achieving satisfactory network performance proved challenging. Consequently, an efficient heuristic algorithm was devised to enhance CRN performance in secure data transfer, incorporating energy harvesting and trust assurance considerations. In 2021, Tayel et al. [70] introduced an Artificial Noise (AN) approach to safeguard the transmission of Secondary Users (SU) against eavesdropper attacks in CR networks with energy harvesting and combined channel access. The initiation of the entire time slot presented challenges for SUs in terms of selecting transmission nodes and managing energy harvesting. To address these challenges, the Mixed Observable Markov Decision Process (MOMDP) was employed to design the decision process for SUs. Simulation results were then conducted to validate the effectiveness of the developed method, considering both throughput and secrecy rate.

In 2021, Bennaceur et al. [71] introduced a hierarchical multi-game theory approach to bolster reputation and trust management in securing the data gathering process. This approach was initiated with spectrum distribution and concluded with data routing. A penalty strategy within the multi-game theory model was employed to identify malicious behavior among nodes through the security safeguard layer in Cognitive Radio Networks (CRN). Experimental evaluations were conducted to demonstrate improved resistance and stability under hostile scenarios. The framework exhibited enhanced efficiency in terms of decision-making, residual energy, and throughput ratio when compared to other benchmark models.

In 2020, Wang et al. [72] introduced Opportunity Routing (OR) within the realm of "Cognitive Radio Social Internet of Things (CR-SIoT)," focusing on the integration of energy awareness and trust to enhance trust and social characteristics. The devised mechanism incorporated a unique routing metric for selecting forwarding candidates based on network coding and optimal stopping theory, facilitating data transmission over trusted nodes to generate diverse flows within the CR-IoT network. Simulation results indicated that the implemented secured OR protocols exhibited excellent performance when assessing factors such as throughput and average delay.

In 2019, Ding et al. [73] devised two distinct user scheduling methods termed "Energy-aware User Scheduling (EaUS) and Channel-aware User Scheduling (CaUS)." In the CaUS approach, an Secondary User (SU) with the optimal SU-Small Base Station (SBS) link was selected for activation to establish communication with the SBS. Conversely, the EaUS method focused on energy harvesting through the Power Transfer (PT) and the quality of the SU-SBS link. The analytical findings affirmed that the EaUS approach exhibited improvements in secrecy and outage performance, while the CaUS approach resulted in a lower secrecy rate.

In 2017, Zhang et al. [74] presented an enhanced solution for the resource allocation problem, aiming to achieve consistency across spectrum sensors and conserve the energy of data sensors. This solution was realized through two algorithms: the "Data Sensor Resource Allocation (DSRA) algorithm" and the "Spectrum Sensor Scheduling (SSS) algorithm." The implemented SSS algorithm estimated channels for the spectrum sensors, leading to higher average recognition time in the channels. Simultaneously, it observed Energy Harvesting (EH) dynamics and secured the transmissions of primary users. The DSRA algorithm managed channels, power, and time to minimize the energy consumption of data sensors. Comprehensive analysis demonstrated a reduction in energy consumption required for data sensors by effectively coordinating sustainability computations for the spectrum sensors. D. T. Hoang et.al. 2015 The authors first formulated the problem of the output optimization of a secondary consumer in a Markov decision process under attack by the jammer (MDP). Then a new solution was introduced based on the disappointing tactic to deal with intelligent jamming. Provide a secondary user learning algorithm to discover the best transmission policy and extend the case in the same environment to many secondary users. By simulating the analysis, the projected learning algorithms will effectively lessen the adverse effects of intelligent jammers even though they are using different attack strategies [75].

IoMT, CRN and Energy Harvesting research are very comprehensive and are facing numerous opportunities and challenges. These two critical approaches to continue improving wireless networks for the future generation still require further scrutiny and study.

Literature review summary table

Author	Methodology	Feature	Challenges
Wang *et al.* [16]	TOT	It enhances the performance of the data transmission and allows the relay packets to reach rapidly to the target at minimum cost.	It is highly prone to various kinds of attacks owing to its dynamic spectrum availability
Dhiman and Sharma [17]	SHO	It benefits in allowing optimum data transmission at the higher level of the network.	It does not consider the channel imperfection effects as its constraint for updating the routing table.

Gopi Krishnan *et al.* [84]	DEDC	It minimizes energy consumption and enhances communication speed.	It does not evaluate based on the hardware implementation and not addressed accuracy.
Vimal *et al.* [85]	MOACO	It improves the lifetime parameters, residual energy, and network lifetime.	Here, the analysis with the traditional models is not performed using the energy parameters in terms of jamming attacks.
Ghose *et al.* [86]	ES and EDT	They strengthen the transmission and do not allow re-transmission. They also secure a slightly higher packet delivery ratio.	They do not consider the effect of interference levels over the concurrent transmissions under the realistic channel scenarios.
Anamalamudi *et al.* [87]	CR-AODV	It achieves satisfying throughput and network energy consumption and reduce nodes.	It is limited in selecting the optimized energy-efficient end-to-end channel route owing to the cognitive control channel saturation.
Fayyaz *et al.* [88]	CR-MAC	It secures high throughput and transmission energy.	It is prone to hacking and damage to the users.
Kumar *et al.* [89]	CDTM	It ensures accurate prediction and reduces the CPU and bandwidth consumption decreasing the analysis time.	It is not applicable in the actual healthcare field for examining the data.
Abd El-Malek et al. [94]	Unconstrained PSO	It provides optimal energy transmitting power and ensures very less system outage performance	It does not focus on route selection and power allocation when operating in underlay nodes
Joon and Tomar [113]	EAQ-AODV	It achieves less minimal time to transfer the data packet, and also it provides enhanced energy	It reduces per-node capacity and also requires more energy for battery powered devices
Jiang et al. [114]	TCEM algorithm	It is feasible and effective to attain high energy efficiency in the network for different destination nodes	The transmission power gets varied to the entire node, and thus, it occurs the generality loss
Banerjee and Maity [53]	Fully EH enabled multi-hop CRN	reduces the outage minimization problem with the consideration of relay	It suffers from the outage secrecy minimization problem with the

		power, source, and relay harvesting time.	increasing of eavesdroppers
Abu Diab et al. [116]	ERCR	It performs a very less number of forwarding nodes for route selection with a limited amount of energy	It is limited while accessing the single wireless channel as the medium access strategy
Cavdar and Güler [117]	HyMPRo	It provides enhanced performance regarding the throughput, end-to end packet delay, and packet delivery ratio	It does not concentrate on involving the multi-path communication mechanism of the model to make it more flexible
Yadav et al. [118]	EACRP	It solves both the dynamic spectrum and energy related challenges	It faces challenges during the high frequency of re-clustering owing to PU activities
Feng et al. (2016)	GSSD	It successfully reduced the success ratio of SSDH attacks. It also reduces trust errors at the time of the low number of SSDH attackers.	When the increasing number of misbehaving nodes is presented in the network, it also leads to an increase in the average delay.
Nguyen et al. (2020)	HSTCN	It is effectively minimizing the performance gap between two users by modifying the coefficient of the power allocation.	It is not evaluated the efficiency of the framework with many NOMA users. It suffers from certain factors like channel quality and power allocation ratios.
Zhang et al. (2017)	SSS and DSRA	It lowers the energy consumption required for the energy sensors at the time of managing the sustainability of the spectrum sensors.	It is not suitable for the environment with adaptive threshold sensors and time-varying energy harvesting in CRN.
Ding et al. (2019)	CaUS and EaUS	It increases security performance even with the increasing number of primary and secondary users.	It is limited to energy harvesting for secondary users.
Tayel et al. (2021)	Hierarchical multi-game scheme	It is efficient in assuring better energy usage and also in providing superior security.	It suffers from performing the beamforming and antenna selection.

CHAPTER 3

INTELLIGENCE-BASED OPTIMIZED COGNITIVE RADIO NETWORK

3.1 Introduction

The Cognitive Radio (CR) structure for organizing and managing healthcare information transfer across the Internet of Medical Things (IoMT) network has been developed in this study. The proposed SR-CHGWO hybrid optimization technique aims to select cluster heads for the purpose of enhancing energy efficiency in cluster-based data transmission. When the proposed optimization algorithm is applied to the derived multi-objective function, it takes into account limitations like throughput, data rate, outage probability, delay, and other issues. This makes the IoT-based Cognitive Radio network last longer. Additionally, the computational complexity of the suggested algorithm is computed and contrasted with that of the traditional optimization algorithm across various medical datasets.

The practical utility of IoT has garnered widespread interest among researchers. Recent technological progressions have resulted in a significant increase in the connectivity of devices to the Internet. Every day, there are a growing number of connectivity issues emerging as a result of the massive rise in the quantity of internet-connected devices (IoT devices). Internet of Things applications are currently deployed across various domains, including smart cities, intelligent transportation, healthcare, agriculture, and other industrial needs. Consequently, there will be large cost and income reductions when these IoT devices or systems are implemented across multiple industries. Because they are necessary for data collection, wireless sensor networks, or WSNs, are crucial to the Internet of Things. WSNs do, however, present several difficulties with regard to energy, spectrum congestion, localization, security, delay, and stability [76]. Because of its explosive growth, researchers are using a range of approaches to mitigate the problems that the Internet of Things is bringing about. One major issue with Internet of Things applications is spectrum band allocation. A great number of IoT devices need constant, everywhere communication, so the available spectrum is insufficient due to overcrowding in the spectral bands. To provide smooth communication between IoT devices, researchers are searching for new spectral bands or workable techniques. Recent IoT adaptations of Cognitive Radio Networks (CRN) have outperformed widely used technologies such as Wi-Fi, Wi-Max, Bluetooth, and others in terms of performance. These networks all use static techniques for allocating spectrum.

Therefore, one of the main challenges is the emergence of opportunistic approaches for controlling and managing Wireless Spectrum Allocation to maximize the limited resources.

The sudden surge in wireless communication networks has limited spectrum resources for apps and their users, making it difficult to connect their interconnected products. Hence, there is a significant rise in demand for intelligent devices capable of adjusting their transmission parameters as per the spectrum availability in spatial and temporal dimensions [77]. A prime candidate for this purpose is Cognitive Radio (CR), characterized as an adaptive and intelligent radio and network technology. It autonomously scans the wireless spectrum to identify available channels and adjusts transmission parameters, enhancing radio operational performance and facilitating increased concurrent communications. On the other side, using unlicensed bands will make coexistence more problematic. Because of this, IoT devices needed additional features to get beyond interference from other apps and devices [78]. Health Information is prevalent in the medical business and has been growing correspondingly. For a more accurate diagnosis, these Health Information must be sent to medical professionals. Furthermore, because IoT nodes and spectrums are diverse and dynamic, designing a routing protocol in CR with their assistance is quite difficult.

3.2 Motivation and Problem Statement

Cognitive Radio technology has the potential to unify patient data within the healthcare sector, enabling its accessibility to global medical specialists. The integration of diverse health information from various sources not only enhances decision-making but also strengthens the overall medical system. Health professionals may now understand several types of Health Information pertaining to a patient's medical status thanks to technology [79]. Additionally, it gathers health information with the use of health observing equipment and transforms it into knowledge that medical professionals may utilize with great benefit [80]. In order to deliver better care, cognitive technology helps physicians make the right judgments by comparing their decisions with the available data. Accessing the opportunistic licensed channel in Cognitive Radio networks does not currently enable global control channels for broadcasting route control messages throughout the entire antenna beam [81]. Deafness and multi-channel concealed terminal issues will also result from the directed broadcast antenna beam over many non-overlapped legal channels. Due to the existence of large number of IoMT Devices there will be a spectrum congestion in the ISM band, this motivated us to search for the other alternate solution to go with the cognitive radio framework which utilize the spectrum efficiently.

3.3 Research contributions

The primary objective of this research is to design and implement an energy-efficient cognitive radio network tailored for the efficient transmission of medical data. This involves the development of a hybrid optimization algorithm, with a focus on achieving optimal energy utilization within the network.

To achieve efficient data transmission, the study proposes the application of the SR-CHGWO algorithm to the cognitive radio network. The main aim is to identify and establish an optimum cluster head, which plays a crucial role in facilitating the effective transmission of health data across the network. The SR-CHGWO algorithm is expected to enhance the overall performance and reliability of data transmission in medical scenarios. Furthermore, the research aims to assess the effectiveness of the proposed algorithm by conducting a comprehensive comparison. Key performance metrics, including throughput, delay, energy consumption, outage probability, and computational complexity, will be evaluated. This comparative analysis will be conducted against other existing conventional optimization methods to gauge the superiority and efficiency of the proposed approach.

A distributed database in the cloud contains an increasing amount of healthcare data that may be shared across medical professionals. Nevertheless, the massive volume of multiorgan zed healthcare data processing and analysis could not be supported by the current system. When relay packets are sent to their destination quickly and cheaply, ToT [82] improves data transmission performance. However, due to its fluctuating spectrum availability, it is extremely vulnerable to several types of assaults. Benefiting from optimal data transmission at the network's upper tier are explained in SHANN and SHO [83]. However, they fail to take into account the constraints imposed by channel imperfection while changing the routing List. DEDC [84] reduces energy usage and speeds up communication. Nevertheless, it ignores accuracy and does not assess depending on hardware implementation. The lifespan parameters, residual energy, and network lifetime are all improved by MOACO [85]. However, in terms of jamming assaults, the analysis with classic models does not use the energy parameters. By fortifying the transmission and preventing retransmission, ES and EDT [86] manage to achieve a somewhat improved packet delivery ratio. Nevertheless, they fail to take into account the impact of interference levels on simultaneous transmissions in practical channel settings. CR-AODV [87] minimizes nodes while achieving acceptable performance and network energy usage. However, because of cognitive control channel saturation, it is constrained in choosing the most end-to-end energy-efficient channel path. High throughput and transmission energy are secured by CR-MAC [88], yet user damage and hacking are possible. To shorten the analysis time, CDTM [89] guarantees precise prediction while consuming less CPU and bandwidth. Nevertheless, it is not useful for looking at the real-world data in the healthcare industry. A new model must be created taking into account these current difficulties in order to transmit health Information using cognitive routing protocols in the Internet of Things.

3.4 IoT Cognitive Routing Framework: An Architectural Overview

An Architectural Overview" refers to a comprehensive examination of the structural design and components of a cognitive routing system specifically tailored for the Internet of Things (IoT) environment. This framework is engineered to optimize the routing of data within IoT networks, considering the dynamic and diverse nature of IoT devices, applications, and communication patterns.

Key components and features of the architectural overview may include:

Cognitive Elements: Explanation of cognitive elements integrated into the routing framework, which may involve adaptive learning algorithms, decision-making processes, and awareness mechanisms.

Routing Protocols: Overview of the routing protocols employed within the framework, discussing how they adapt to varying network conditions, device capabilities, and application requirements.

Data Aggregation and Processing: Description of mechanisms for aggregating and processing IoT data efficiently, considering the distributed nature of IoT devices and the need for optimized information flow.

Adaptability and Learning: Discussion on how the routing framework adapts to changes in the IoT environment, leveraging machine learning or cognitive computing to enhance decision-making based on historical data and real-time conditions.

Security Measures: Insight into the security features embedded in the architecture to safeguard IoT communication, addressing potential vulnerabilities and ensuring the integrity and confidentiality of transmitted data.

Scalability and Flexibility: Examination of the framework's scalability to accommodate a growing number of IoT devices and its flexibility to support diverse IoT applications and use cases.

Interoperability: Consideration of how the cognitive routing framework facilitates interoperability among different IoT devices, protocols, and communication standards.

Real-world Applications: Illustrative examples or case studies showcasing how the proposed cognitive routing framework can be applied in real-world IoT scenarios, with a focus on the medical sector or other relevant domains.

Performance Metrics: Identification and discussion of key performance metrics used to evaluate the effectiveness of the cognitive routing framework, such as latency, throughput, energy efficiency, Hop count, Outage probability and reliability.

Considerations such as node energy utilization, overall packet delays, and throughput of the network are essential for achieving this optimization. The "Common Control Channel (CCC)" proves valuable for robust route discovery and maintenance during packet transmission. The introduction of directional antennas enhances simultaneous non-interfering channel transmission in cognitive radio networks, minimizing node power consumption and improving overall throughput through spatial reuse in multi-hop communication.

Conversely, directional antennas are crucial for reducing interference and enhancing throughput in IoT applications and directional cognitive control. Traditional routing protocols in cognitive-based IoT networks often use omnidirectional transmission for message exchange, leading to packet loss and route failures due to co-channel interference when handling both primary and secondary users. Secondary users, without licenses, access radio frequencies without interfering with networks, while primary users adhere to licensed frequency usage. To mitigate interference with primary networks, these users connect to a base station, which serves as a central hub for consolidating remarks and spectrum analysis findings from each CR user. The overall design of cognitive routing in the Internet of Things is depicted in Fig 3.1.

The unlicensed group, representing secondary users, strategically utilizes the resources of licensed primary users in Fig 3.1. This strategic utilization occurs in the absence of primary users, ensuring efficient spectrum utilization for sensor nodes within the Internet of Things (IoT) network. Within this network, the cluster head plays a pivotal role in collecting sensor data and making use of the unused spectral bands from the primary network to transmit aggregated data to the base station.

Each cluster head operates as a Cognitive Internet of Medical Things (IoMT) device, facilitating the transfer of data collected from sensor nodes to the central base station. This collective effort among cluster leaders contributes significantly to the establishment and operation of a cognitive radio network. In this configuration, primary users, depicted as licensed users, and secondary users, forming the unlicensed group, collaboratively shape the dynamic spectrum utilization within the IoT network.

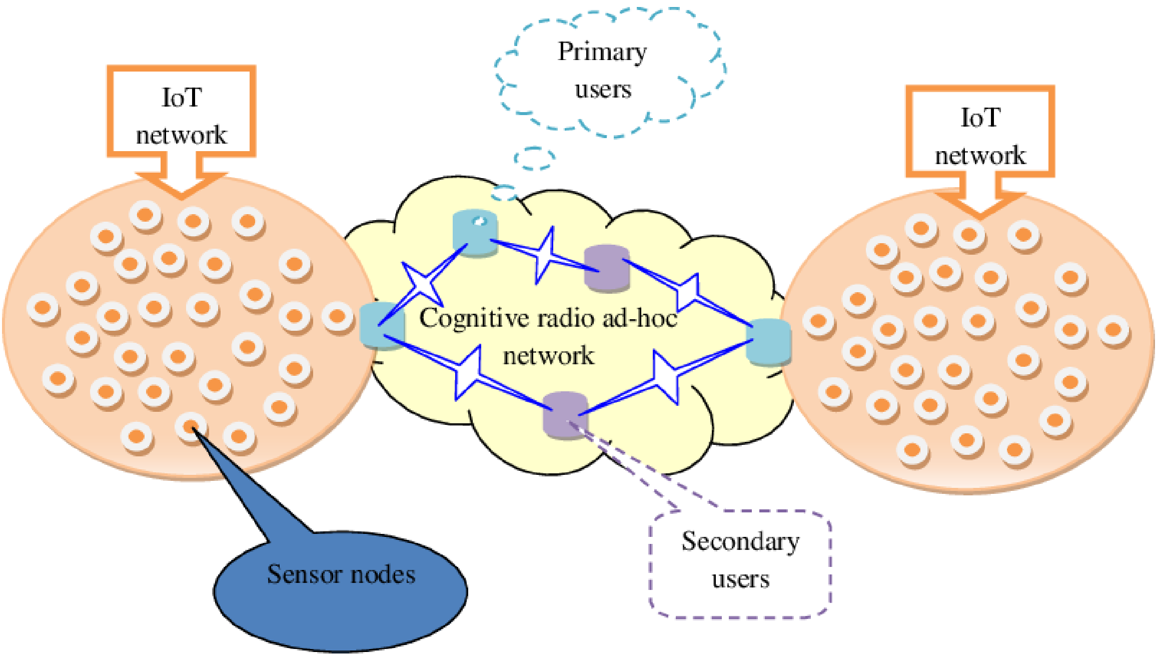


Fig.3.1 Architectural Landscape of Cognitive Routing in IoT.

3.5 Advanced CR Routing Solution for Efficient Health data Transmission

The growing reliance on wireless devices has spurred an increased need for enhanced internet access via wireless networks. Nonetheless, challenges arise for Internet of Things (IoT) devices with limited battery life and applications that demand minimal delays. While some IoT applications can tolerate delays, there is acknowledgment that the technology holds potential for energy-aware cognitive radio routing protocols within multi-hop Cognitive Radio Networks (CRNs). Unlike battery-dependent devices, numerous IoT devices operate without energy restrictions, rendering them well-suited for sensitive applications like smart grids. This underscores the necessity for a CR routing system that effectively balances delay efficiency, particularly in applications of process automation, which may permit slightly longer time utilization.

Recognizing the vulnerability of CRNs to network disruptions caused by a single device's energy depletion, Figure 2 emphasizes the imperative for an efficient cognitive routing protocol to address prevailing IoT-related challenges. To facilitate the streamlined transmission of Health Information across the network with minimal information loss or delay, a novel cognitive radio routing architecture for the Internet of Things has been conceived. This entails the application of a hybrid optimization technique for optimal cluster head selection, utilizing the developed SR-CHGWO. The selection process takes into account of multi-objective limitations, including throughput, energy consumption, data rate, outage probability, and delay.

This comprehensive approach contributes to the effective transfer of medical data, improving the performance of health data transmission by minimizing power and delay throughout the Internet of Medical Things (IoMT) network. Ultimately, this aids in extending the network's lifetime and mitigating transmission delays.

3.5.1 Description of Health Information

In order to transmit medical data, the suggested energy efficient routing method gathers health information from three distinct datasets and they are described below.

The first medical dataset, referred to as 'Diabetes Dataset' (Dataset 1), consists of diabetic diagnosis data from female patients under the age of 21 years. It includes 768 instances and encompasses more than 8 classes, providing a detailed description of the patient's diabetic condition.

The second dataset, named 'Heart Disease Dataset' (Dataset 2), comprises a total of 76 properties, with only 14 of them utilized in published studies. The 'target' field indicates the patient's cardiac condition, with 0 denoting no illness and 1 denoting the presence of disease.

The third dataset, titled 'Indian Liver Patient Records' (Dataset 3), is derived from 416 liver patient records and 167 records from individuals without liver disorders. The dataset categorizes them into 2 groups: non-liver patient's, liver patients.

The links for the data sets are given as mentioned below.

Dataset1: https://www.kaggle.com/datasets/mathchi/diabetes-data-set

Dataset2: https://www.kaggle.com/code/vbmokin/heart-disease-automatic-adveda-fe-20-models

Dataset3: https://www.kaggle.com/datasets/uciml/indian-liver-patient-records

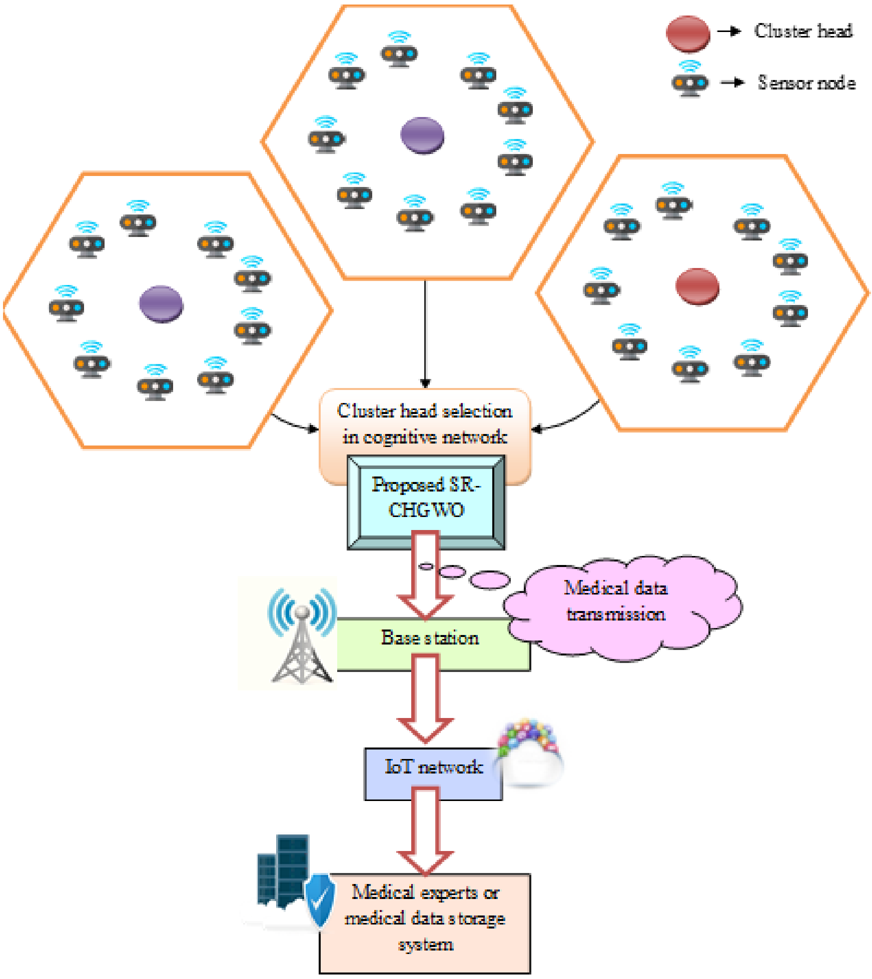


Fig.3.2 Flow of CR Routing protocol within the IoT network.

3.5.2 Cluster Head selection

Utilizing the proposed SR-CHGWO algorithm, clustering emerges as a recognized technique for enhancing the longevity of wireless communication networks. This method involves organizing sensor nodes into clusters, with the algorithm determining the optimal cluster heads. Once formed, each cluster, under the direction of its cluster head, establishes a designated timeframe for receiving data packets from various nodes within the cluster. The primary responsibility of each cluster head is to collect data packets from every node within the cluster.

Following data aggregation, if all nodes successfully receive all the data packets, CH node transmits the Health Information to the PU base station. This process undergoes several iterations of data transmission and re-clustering until all nodes are terminated. In cases where the cluster size falls below the expected threshold, clusters are merged with nearby clusters, effectively reducing the overall number of clusters. Simultaneously, as the number of nodes in the physical realm decreases, there is a proportional reduction in the volume of transmitted information.

3.5.3 Proposed Algorithm and its Description

To achieve energy-efficient transmission of Health Information in the Internet of Things (IoT) through Cognitive Radio (CR), a hybrid version of the SR-CHGWO algorithm [90] is employed for cluster head selection. In this context, the Grey Wolf Optimizer (GWO) is chosen due to its ability to overcome local optima problems and minimize searching dimensions, enhancing convergence rates. However, GWO has limitations in addressing local searches and accuracy issues. To mitigate these concerns, the decision is made to integrate SR-CHGWO with the Comprehensive Harmony Search (CHIO) algorithm. CHIO is specifically applied to resolve the early convergence problems. The proposed SR-CHGWO demonstrates enhanced performance in Health Information transmission within CR based IoT applications. Calculation of the spreading rate in CHIO will be facilitated through the fitness-based methodology presented in Eq. (3.1) within the proposed SR-CHGWO, ensuring more effective and accurate results.

$$Spr = \frac{bestfit}{meanfit} \tag{3.1}$$

The parameters 'mean fit' and 'best fit' in the above equation denote the average of fitness and best value of the fitness for the solution, respectively. The Spr (spreading rate parameter) is employed to ascertain the update of the position. The position is updated using the CHIO algorithm if (Spr > 0.5); otherwise, it is updated using the GWO.

CHIO [91] draws inspiration from the observation of herd immunity, a mechanism known for halting the spread of the coronavirus pandemic. The CHIO process involves two distinct sets of parameters: control and algorithmic. Under control parameters, the spreading rate (basic reproduction rate) Spr, representing the rate of virus transmission from one individual to another, is calculated using Eq (3.1). The Maximum Age (MA) is simultaneously calculated to determine the status of an affected individual based on their infection age.

Moving to algorithm variables, initially affected individuals are represented by A_0 and maximum number of iterations is denoted as MX_{it}, and the herd immunity population is denoted by H_{ps}. In this context, optimum solution for CHIO is obtained by adhering to the following three rules outlined in Eq. (3.2) [21].

$$xx_0^b(it+1) \leftarrow \begin{cases} xx_0^b(it) & rr \geq Spr \\ A\left(xx_0^b(it)\right) & rr < \frac{1}{3} \times Spr \quad //inf\ e\ ctedcase \\ M\left(xx_0^b(it)\right) & rr < \frac{2}{3} \times Spr \quad //susceptiblecase \\ Q\left(xx_0^b(it)\right) & rr < Spr \quad //immunecase \end{cases} \quad 3.2)$$

In this context, the term '$xx_0^b(it)$' represents herd immunity solution, where the decision parameter is set to '0' with solution 'b' at the present iteration. The Status vector S_v undergoes variation in these 3 cases. For the infected scenario, the S_v is assigned a value of 1, while it is set to 0 for susceptible cases. For the immune case, the S_v will be updated according to the fitness value. Subsequently, rate of fatality is examined to determine the number of deceased and immune persons. The iteration is concluded when the population under herd immunity exclusively comprises immune or susceptible cases, with no instances of infection.

GWO [92] is formulated based on the hunting tactics observed in grey wolves, characterized by a four-tiered prevailing social order. The hunting habits of the grey wolf is delineated into three distinct phases: "tracking, chasing, and approaching the prey," followed by "pursuing, encircling, and harassing the prey until it stops moving," and ultimately culminating in "attacks towards the prey." The levels of wolves in the hierarchy, namely alpha, beta, omega, and delta, are respectively denoted by ,α ,β ,δ and ω . The encircling behavior of grey wolves as they pursue prey for sustenance is mathematically expressed in Eq. (3.3).

$$\vec{Ep} = \left|\vec{F}i \cdot \vec{Y}u_p(y) - \vec{Y}u(y)\right| \tag{3.3}$$

$$\vec{Y}u(y+1) = \vec{Y}u_p(y) - \vec{B}t \cdot \vec{Ep} \tag{3.4}$$

In this scenario, the current iteration is symbolized by y , the grey wolf's location is denoted as $\vec{Y}u$, and the prey's location is identified as $\vec{Y}u_p$. Coefficient vectors, represented by $\vec{F}i$ and $\vec{B}t$, are provided. The identification of the prey's location includes the utilization of three positions from the most effective search agents, subsequently used to update the grey wolf's position based on equation (3.5).

$$\vec{Y}u(y+1) = \frac{\vec{Y}u_1 + \vec{Y}u_2 + \vec{Y}u_3}{3} \tag{3.5}$$

$$\vec{Y}u_1 = \vec{Y}u_\alpha - \vec{E}p_1 \cdot \left(\vec{E}p_\alpha\right), \vec{Y}u_2 = \vec{Y}u_\beta - \vec{E}p_2 \cdot \left(\vec{E}p_\beta\right),$$

$$\vec{Y}u_3 = \vec{Y}u_\delta - \vec{E}p_3 \cdot \left(\vec{E}p_\delta\right) \tag{3.6}$$

Here, $\vec{Y}u(y+1)$ term shows the updated location of the grey wolf. Thus, the optimal solution is obtained. The various steps involved in the SR-CHGWO are summarized.

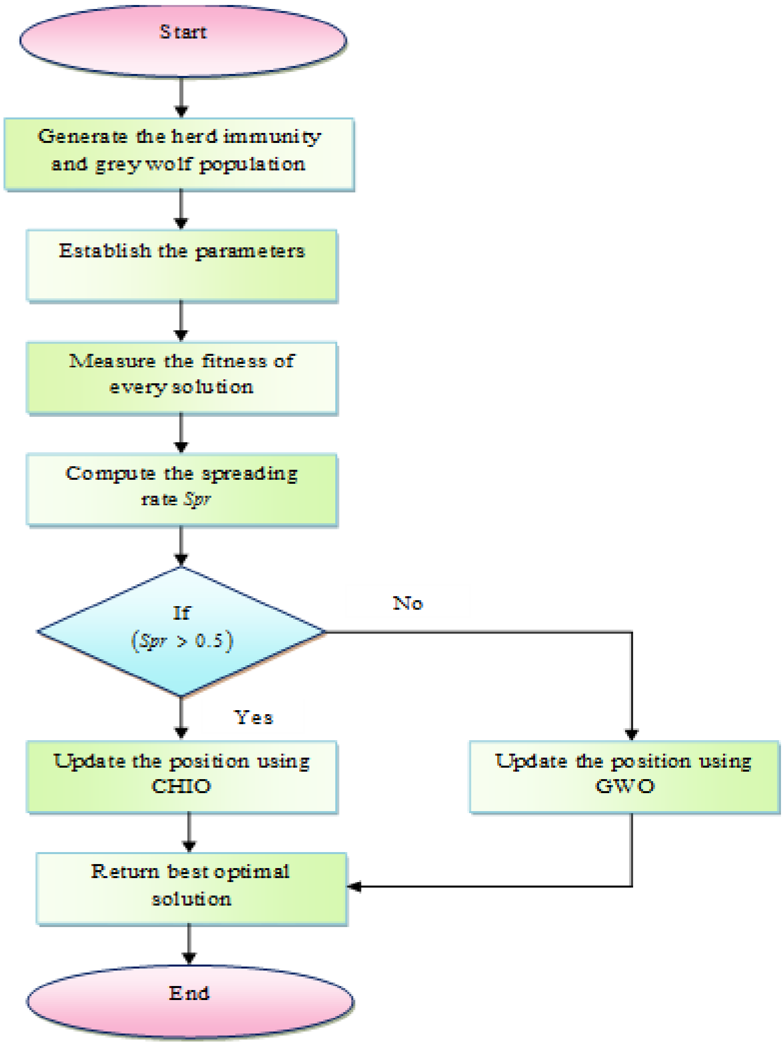


Fig.3.3 Flow chart of the proposed SR-CHGWO

Algorithm for SR-CHGWO

Step1: Defining the Population size and Parameter Initialization:

- Along with the required parameters, define the population size.

Step 2: Initialize Herd Immunity Solution and Best Search Agents:

- Set up the initial herd immunity solution in CHIO.
- Initialize the best search agents of GWO.

Step 3: Determine the Best Solution:

- Compute the fitness of each search agent.
- Calculate the spreading rate using Eq. (3.1).

Step 4: Update Position Based on Spreading Rate:

- If (Spr > 0.5),
  - Update the position using CHIO.
    - Upgrade the location of the solution according to Eq. (3.2).

else,

- Update the position using GWO.
  - Upgrade the location of the solution according to Eq. (3.5).

Step 5: Return the Best Solution:

- Return the best solution obtained.

3.5.4 Multi Objective Optimization function

Multi-objective optimization (MOO) is a technique used to optimize two or more conflicting objectives simultaneously. It involves finding a set of solutions that optimize one objective without compromising the optimization of the other objectives. In MOO, these solutions are often represented as a set of non-dominated points in a high-dimensional space, known as the Pareto front.

Once the Pareto front is generated, the decision-maker can choose the best solution based on their preferences and requirements. For example, if the company is willing to pay a higher cost for better performance, they can select a solution that lies on the Pareto front closer to the performance axis. Conversely, if the company wants to minimize the cost, they can select a solution that lies on the Pareto front closer to the cost axis.

Multi-objective optimization is a powerful technique used to solve complex problems that involve multiple conflicting objectives. By finding the set of non-dominated solutions, MOO allows decision-makers to make informed trade-offs between the objectives and select the optimal solution that best meets their needs.

The suggested Health Information transmission approach in the Internet of Things (IoT), employing CR (Cognitive Radio), is executed through the devised SR-CHGWO. This method is employed to identify the most efficient route for sending the data from source to the target nodes. The optimization process considers multiple objectives, encompassing " throughput energy consumption, Network delay , data rate and outage probability." The primary objective of the proposed routing protocol is formally defined in Eq.(3.7)

$$Bn = \underset{\{CH_o\}}{argmin}(f_7) \tag{3.7}$$

The designated cluster head in the context of Health Information transmission is denoted as CH_o, facilitated by the innovative SR-CHGWO. The attainment of objective f_7 is determined by the equations outlined below. These equations are derived from the reference [93] and are employed for the purpose of selecting the cluster head. The above function is a minimization function. Cluster Head is selected in such a way that it minimizes the objectives defined by equation 3.7.

$$fitness = w * g_1 + (w - 1) * g_2 \qquad 0 < w < 1$$

Where g_1 and g_2 are the objective constraints, and w is the weighing factor distributed among two constraints $g_1$and g_2.

$$f = P * \left(\frac{1}{dis}\right) + (1 - P)*\text{en} \tag{3.8}$$

$$f_1 = Q * f + (1 - Q) * \left(\frac{1}{dis}\right) \tag{3.9}$$

$$f_2 = R * f_1 + (1 - R) * (en) \tag{3.10}$$

$$f_3 = S * f_2 + (1 - S) * (thr) \tag{3.11}$$

$$f_4 = T * f_3 + (1 - T) * (datarate) \tag{3.12}$$

$$f_5 = U * f_4 + (1 - U) * (Pwr) \tag{3.13}$$

$$f_6 = Q_1 * f_5 + (1 - Q_1) * \left(\frac{1}{Opr}\right) \tag{3.14}$$

$$f_7 = Q_2 * f_6 + (1 - Q_2) * \left(\frac{1}{delay}\right) \tag{3.15}$$

The preceding equations were deduced from the principles of multi-objective optimization, utilizing both minimization and maximization functions. In this context, the value (P) and the value (Q) are set to 0.2. Additional constraints, such as R, S, T, U, Q_1, and Q_2, are consistently established at fixed values of 0.1 each.

3.5.4.1 Description of Objective Constraints

The following paragraph elucidates the specified limiting factors, such as " throughput energy consumption, Network delay , data rate and outage probability" that pertain to the stated objectives.

Energy, denoted as 'en,' is obtained by calculating the average energy level present in a live node at the end of the experiment. As given in Eq. (3.16).

$$en = en_{nj} - \left(ei_{nj}^{cs} + ei_{nj}^{sh}\right) \tag{3.16}$$

In this context, the energy utilized during data collection is represented as ei_{nj}^{cs}, the energy of any node nj is denoted as en_{nj}, the energy used for the transmission of data is expressed as ei_{nj}^{sh}. Equation (3.17) represents distance (dis) between the source and the target nodes.

$$dis = \sqrt{\sum_{m=1}^{M}(Ai_{an} - Aj_{an})^2} \tag{3.17}$$

Here, the Originating node is represented as $nd_1 = (Ai_1, Ai_2, \dots Ai_{an})$ while the sink node is expressed as $nd_2 = (Aj_1, Aj_2, \dots, Aj_{an})$.

Throughput (thr) refers to the rate of successful message delivery or data transfer over the network within a specified timeframe. It is a measure of the amount of data transmitted successfully from source to destination nodes.” which is indicated in Eq. (3.18).

$$thr = \frac{\sum(Pi_{sc} * aP_{sz})}{tme} \tag{3.18}$$

The term aP_{sz} denotes the average packet size and Pi_{sc} indicates the successful packets count. Delay ($delay$) is computed by evaluating the propagation and transmission delay within the packets as indicated in Eq. (19).

$$delay = \frac{max \sum_{k=1}^{K} SP_k}{nj} \tag{3.19}$$

Term $max \sum_{k=1}^{K} SP_k$ represents data sent between base station and sensor node; node count in the network is indicated as nj.

Data rate ($datarate$) is defined as “the amount of data sent during a specified time interval over a network. It is the speed at which data is transferred from one device to another”.

Transmit power control Pwr, serves as a technical mechanism implemented in certain networking devices to mitigate excessive interference between distinct wireless networks, such as the owner's network and neighboring networks. This functionality is crucial, especially in the deployment of cognitive radio networks operating in a distributed fashion.

Outage probability Opr in cognitive radio networks refers to the probability of the communication link falling short of predefined thresholds. In the dynamic spectrum access environment of cognitive radio, outage probability is frequently associated with the chance of being unable to locate appropriate spectrum bands for communication due to issues like interference, limited spectrum availability, or environmental factors. This metric quantifies the likelihood of either a communication link experiencing difficulties in sustaining a dependable connection or achieving desired quality of service benchmarks within a specified timeframe.

Table 3.1. Parameters and their description

Parameter	Description
Spr	Spreading Rate
rr	Basic Reproduction Rate
A_0	Initial Population
$A(xx^b_o(it))$	Herd immunity solution (infected case) First solution (status vector s_v=0 or 1)
it	Iteration count (maximum =100)
$Q\ (xx^b_o(it))$	Immune case solution (2^{nd} best solution)
$M(xx^b_o(it))$	Susceptible case solution (third best solution)
en	Average energy in the live node
dis	Distance among the source and destination
thr	Throughput
Delay	Propagation delay
Opr	Outage Probability
pwr	Transmit power control

3.6 Results and discussions

3.6.1 Experimental Configuration

The CR-based Health Information transmission network, as outlined in this study, is deployed within a 100m × 100m environment using MATLAB 2021a. The experiment involves a population size of 10 individuals undergoing 100 iterations. To evaluate the effectiveness of the proposed SR-CHGWO method, a comparative analysis is conducted against established heuristic algorithms, including Particle Swarm Optimization (PSO) [94], Jaya Algorithm (JA) [95], Grey Wolf Optimizer (GWO) [92], and CHIO [91]. This comparison aims to assess the efficiency of the devised approach in facilitating reliable Health Information transmission. The simulation parameters of the cognitive radio network are summarize in table 3.2.

Table 3.2 Simulation Parameters

Parameter	Value
Network Dimension	100mX100m
No of secondary Nodes	50,100,150
Node Deployment	Random
Path loss exponent	2
Initial Energy of the node	0.3 Joule
Transmitter/ receiver energy (ETx and ERx)	50 pJ
Data Aggregation Energy	5pJ
Population Size	10
Number of Iterations	100

3.6.2 Cost function Observations with Varied Node Counts

Dataset-1: The evaluation of the IoMT-based Health Information transmission system incorporating CR technology involved an analysis with an increased iteration count, reaching up to 100, as depicted in Fig.3.4 Examining the cost function across three different node scenarios, the developed method demonstrated enhanced performance specifically at a node count of 50 compared to the other two node analyses. Notably, the minimum cost function was achieved at the 40^{th} iteration and further reduced to the lowest value when compared to alternative algorithms at the 100th iteration. Consequently, it is affirmed that the proposed Health Information transmission approach for IoMT devices, utilizing cognitive routing strategies, exhibits effective performance without encountering interference.

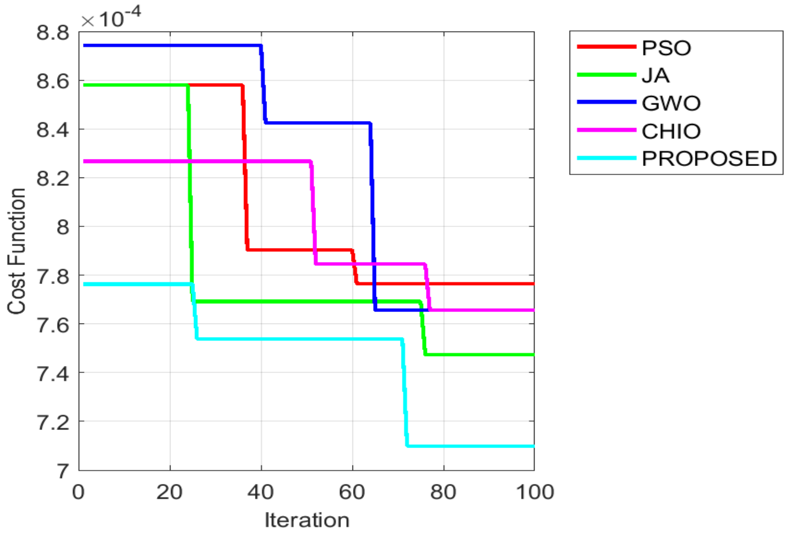


Fig. 3.4(a) Convergence analysis (Dataset-1) with 50 Nodes

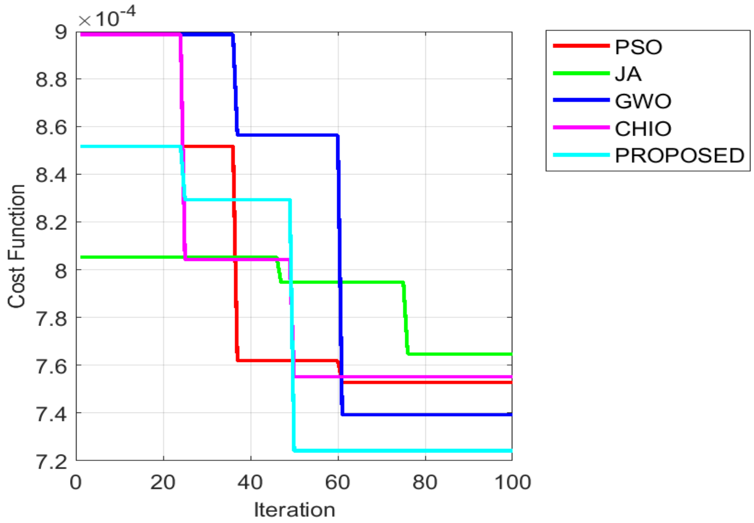


Fig. 3.4(b) Convergence analysis (Dataset-1) with 100 Nodes

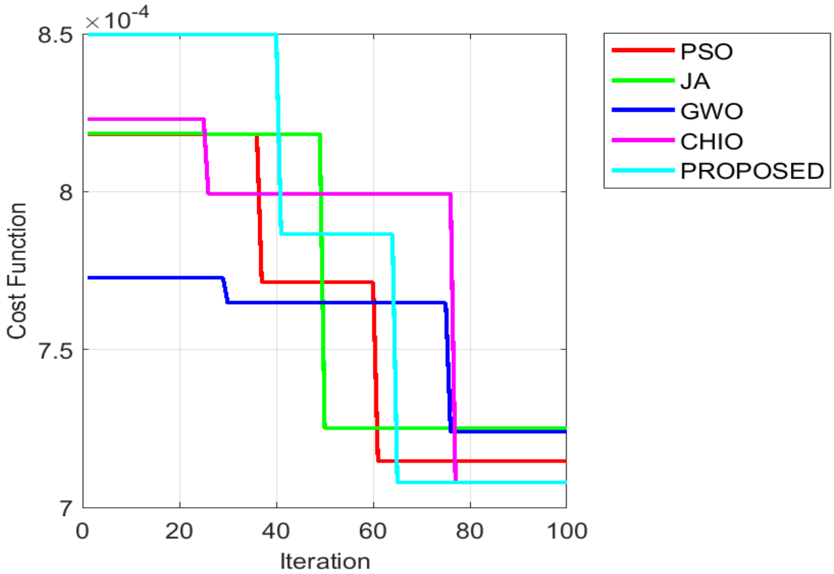


Fig. 3.4(c) Convergence analysis (Dataset-1) with 150 Nodes

Dataset-2: The assessment of the devised CR routing protocol involves a comparison with traditional algorithms by varying the iterations using dataset 2, as illustrated in Fig.3.6. Notably, the devised SR-CHGWO exhibits superior performance against other algorithms such as PSO, JA, GWO, and CHIO, as evidenced by the analysis conducted with a node count of 50. Additionally, when evaluating the proposed model with 100 nodes, it demonstrates excellent performance within the iteration range of 80 to 100. This observation underscores the improved performance of the suggested method as the iteration count increases.

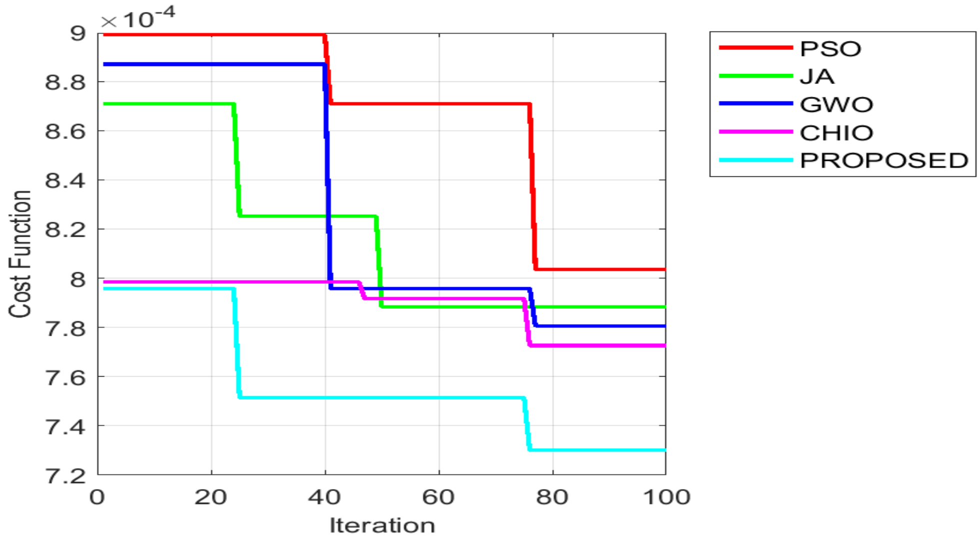


Fig.3.5(a) Convergence analysis (Dataset-2) with 50 Nodes

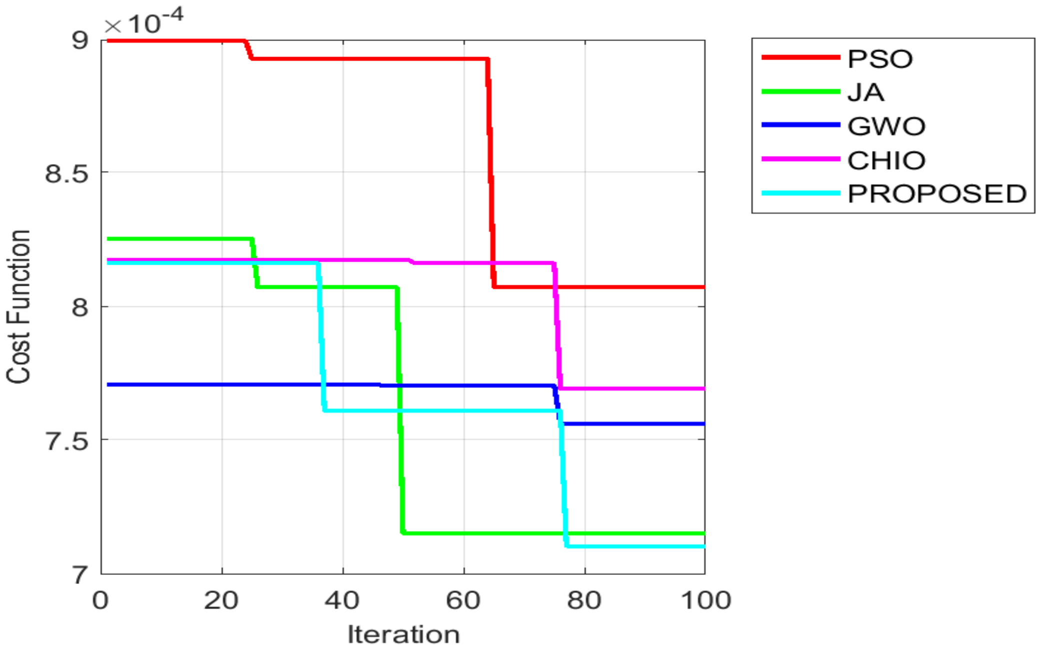


Fig.3.5(b) Convergence analysis (Dataset-2) with 100 Nodes

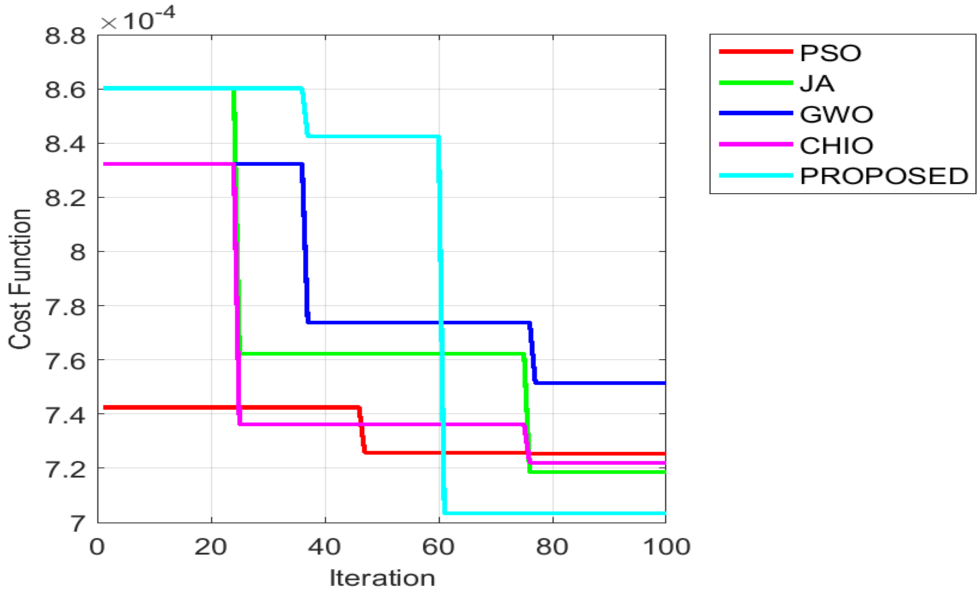


Fig. 3.5(c) Convergence analysis (Dataset-2) with 150 Nodes

Dataset-3 : The suggested cognitive routing in IoMT for Health Information transmission is compared with the baseline algorithms like PSO, JA, GWO and CHIO for understanding the effectiveness of the proposed model that is described in Fig.3.7. The number of 50, 100, 150 nodes are given into analysis that shows when the number of 100 nodes is provided into the network, efficient performance is observed, in which cost function minimization is attained through all the iterations.

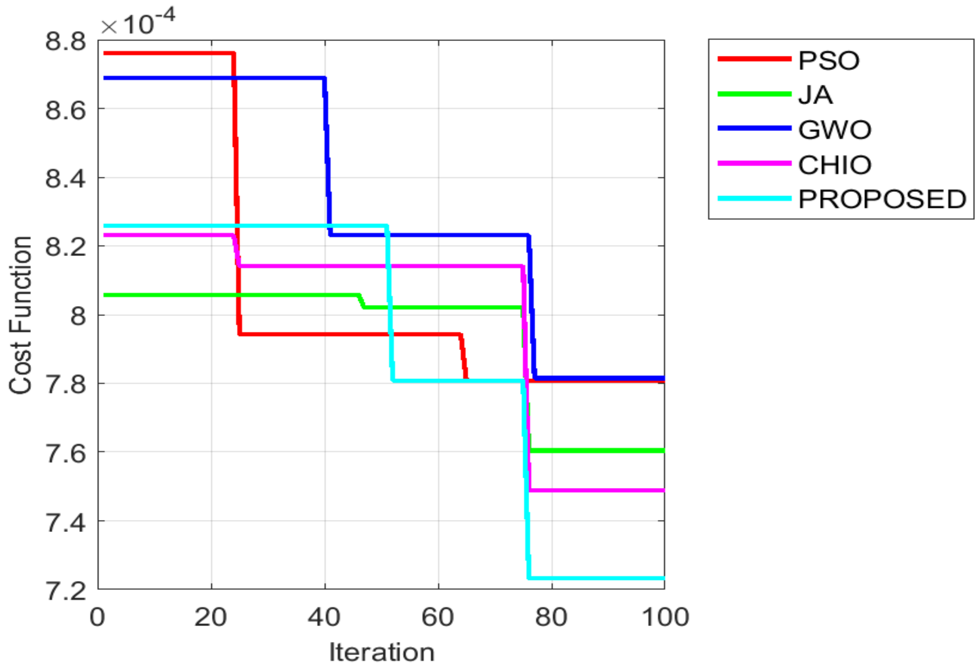


Fig.3.6 (a) Convergence analysis (Dataset-3) with 50 Nodes

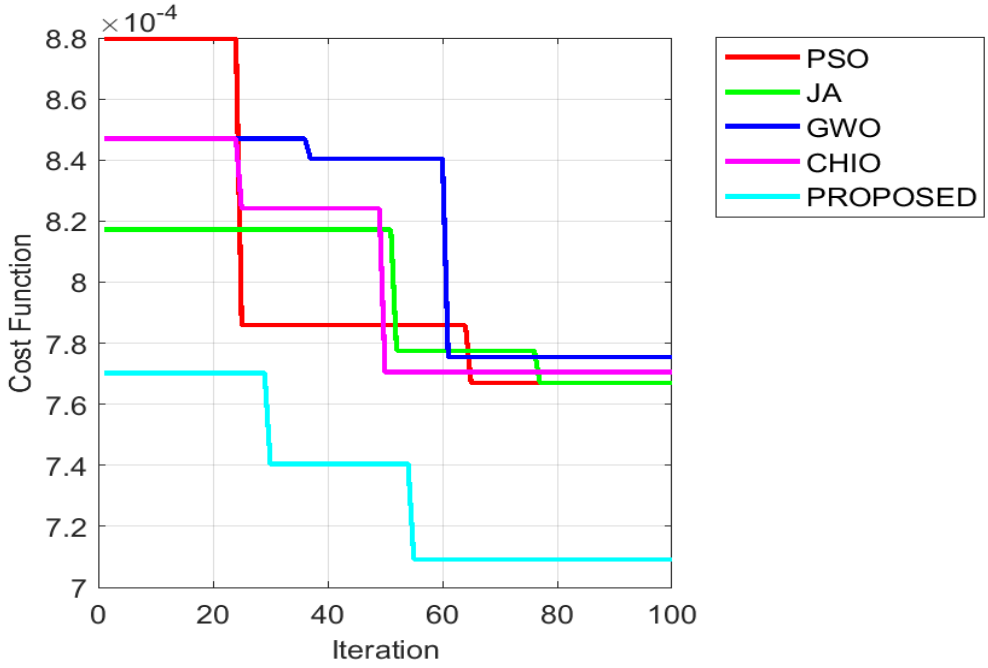


Fig.3.6 (b) Convergence analysis (Dataset-3) with 100 Nodes

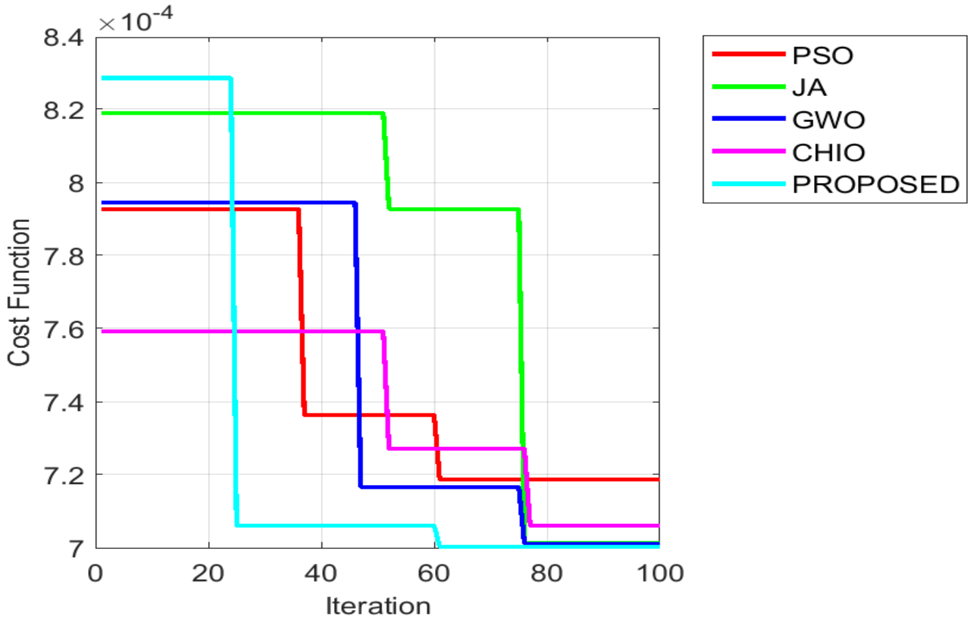
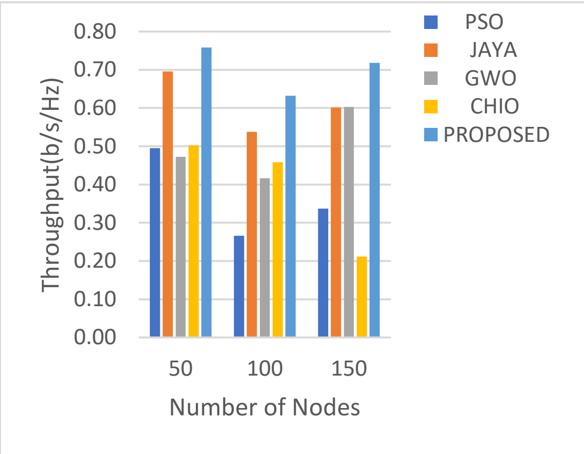


Fig.3.6 (c) Convergence analysis (Dataset-3) with 150 Nodes

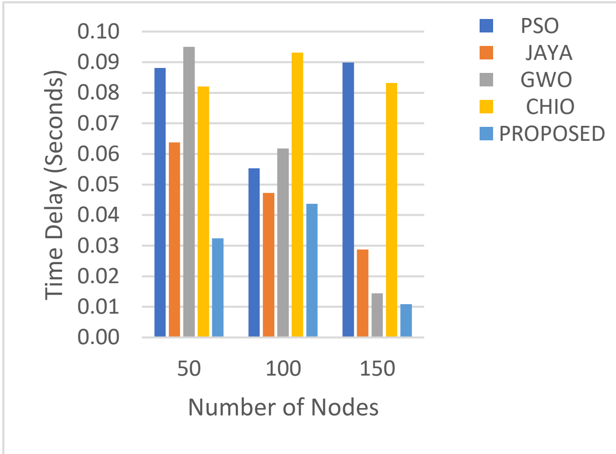
3.6.3 Performance analysis of the proposed Algorithm

Dataset-1: Utilizing the developed SR-CHGWO for Health Information transmission to ensure effective communication is depicted in Fig. 8. The analysis table presented unveils notable advantages in the proposed model, showcasing power consumption percentages that are 6.7%, 4.50%, 7.13%, and 4.30% lesser than those of PSO, JA, GWO, and CHIO respectively.

Furthermore, in terms of time requirements, the proposed model demonstrates significantly reduced durations for Health Information transmission compared to alternative algorithms. The computation complexity of the proposed algorithm, evaluated in simulation time, is observed to be 7.88% lower than that of JAYA. Consequently, these findings affirm the greater performance of the suggested method against other algorithms.



(a)



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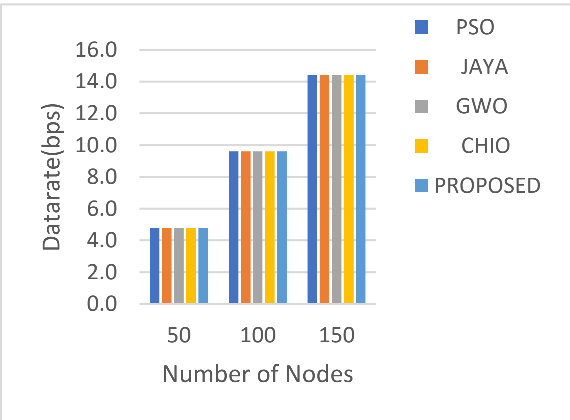
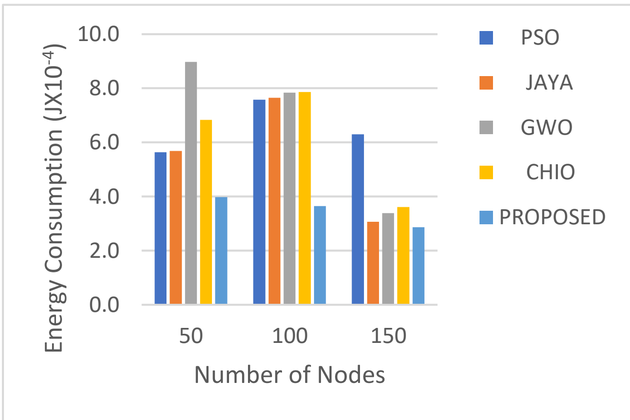
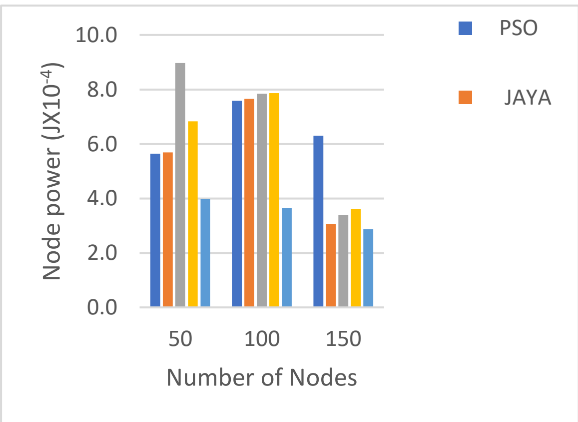


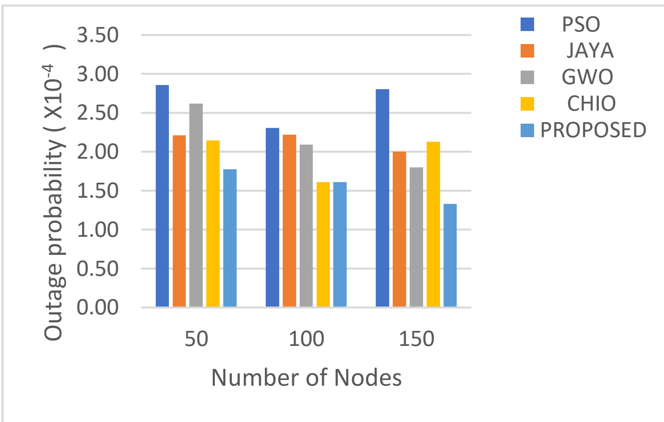
(c)



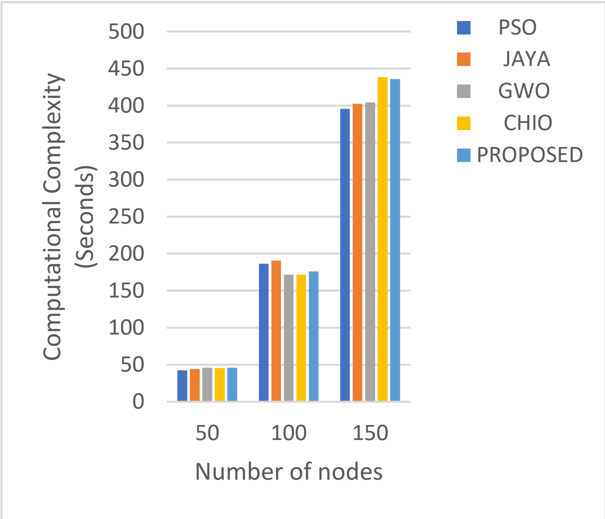
(d)



(e)



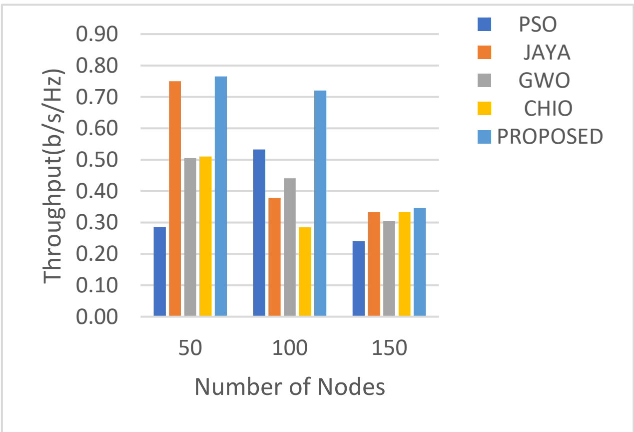
(f)



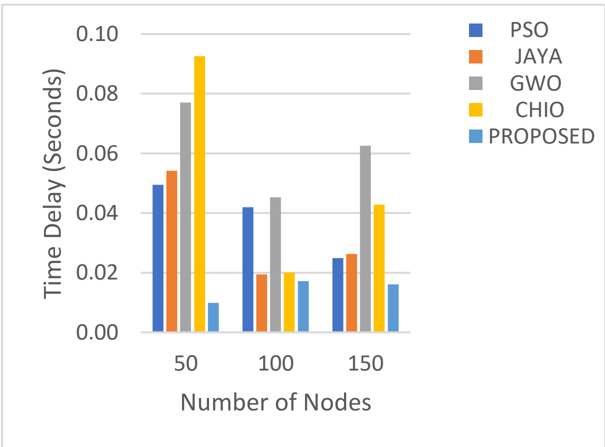
(g)

Fig. 3.7 Performance analysis of the algorithm (Dataset-2) in terms of "(a) throughput, (b) time delay, (c) data rate, (d) energy consumption, (e) node power, (f) outage probability and (g) Computational Complexity"

Dataset-2: The cognitive routing in the IoMT network, based on the developed SR-CHGWO, undergoes analysis using dataset 2, addressing various parameters such as data rate, node power, time consumption, outage probability, and throughput, as illustrated in Fig.3.9. Notable improvements in throughput are evident, surpassing conventional techniques by 6.60%, 7.80%, 5.30%, and 7.40% when compared to PSO, JA, GWO, and CHIO respectively. The computation complexity of the proposed algorithm is assessed and found to be 3.11% lower than that of GWO. Furthermore, across all analyses conducted on dataset 2, the performance of the proposed method demonstrates enhancement when contrasted with existing algorithms.



(a)



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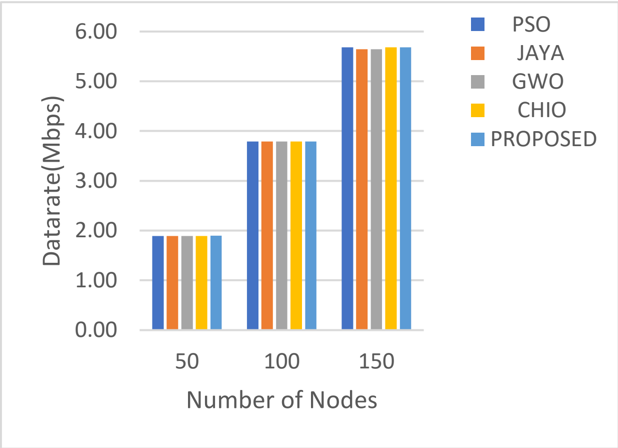

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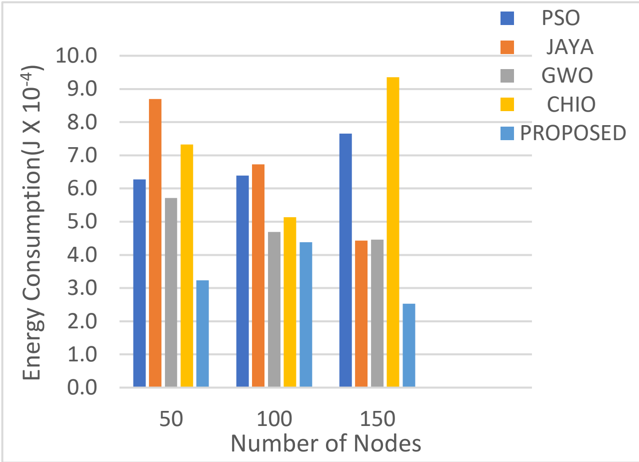

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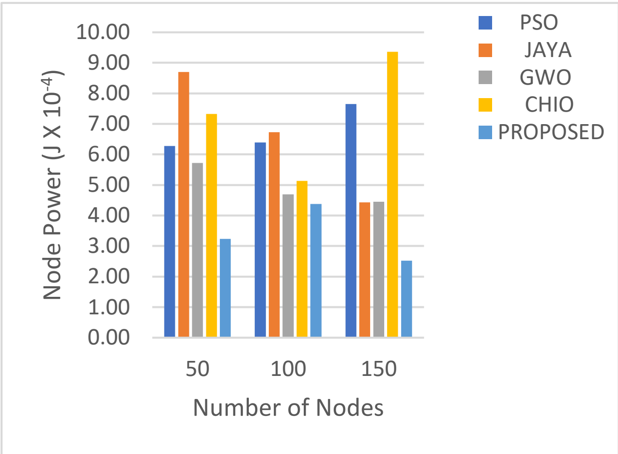

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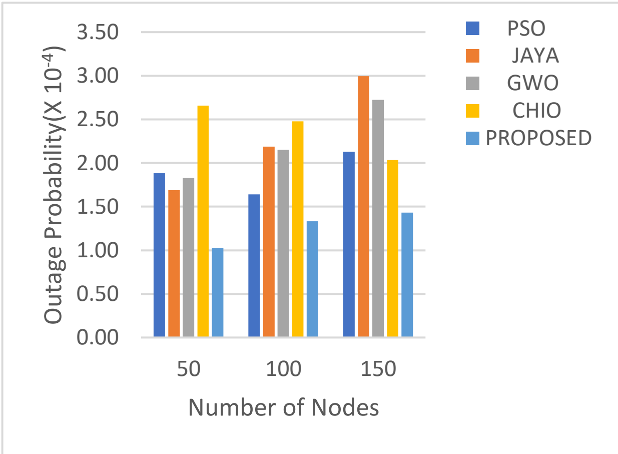

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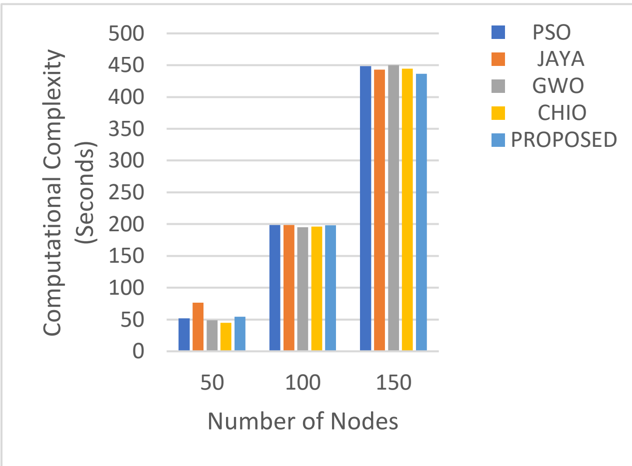
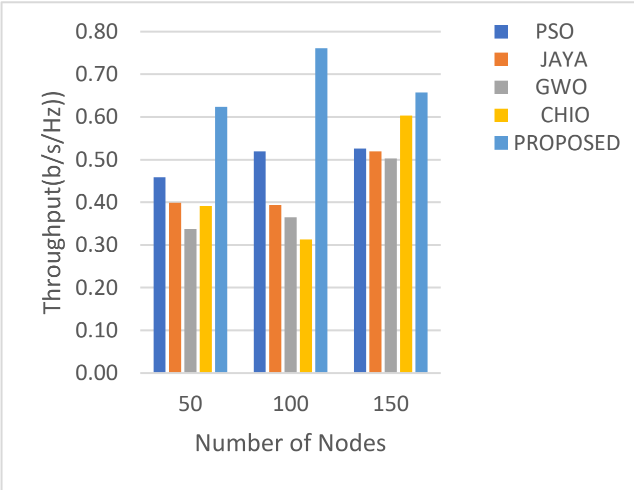


(g)

Fig. 3.8 Performance analysis of the algorithm (Dataset-2) in terms of "(a) throughput, (b) time delay, (c) data rate, (d) energy consumption, (e) node power, (f) outage probability and (g) Computational Complexity"

Dataset-3: The evaluation of the SR-CHGWO for Health Information transmission involves a comparative analysis with established algorithms, including PSO, JA, GWO, and CHIO, based on dataset 3, as depicted in Fig.3.10. The assessment aims to showcase the efficiency of the developed routing technique by conducting node analyses at 50, 100, and 150. In this comparison between the proposed and conventional algorithms, SR-CHGWO consistently demonstrates proficient performance in transmitting Health Information through IoMT devices, proving to be more effective than the established algorithms.



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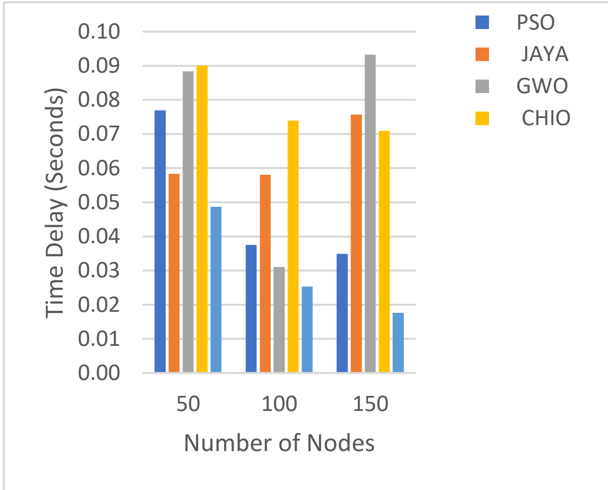

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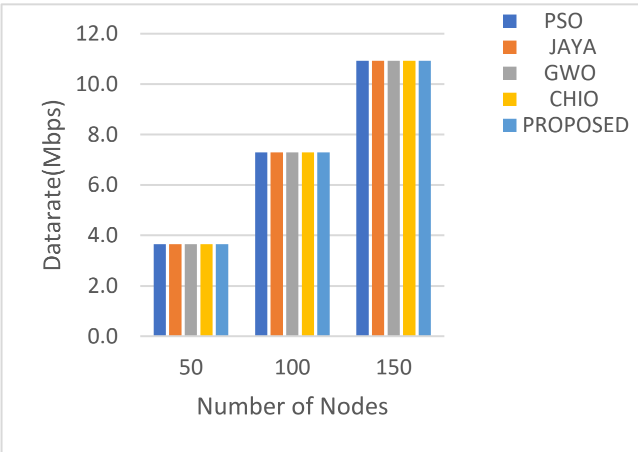

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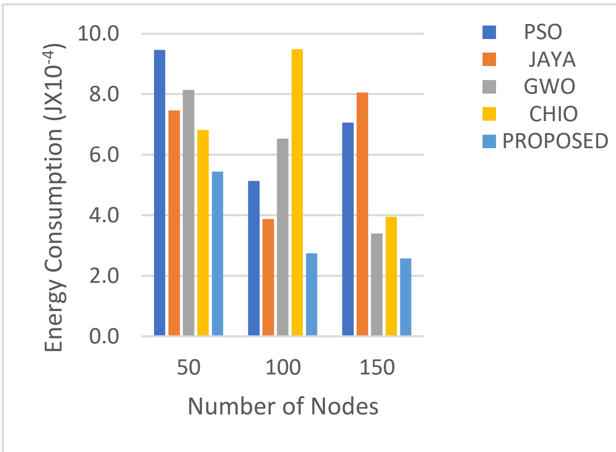

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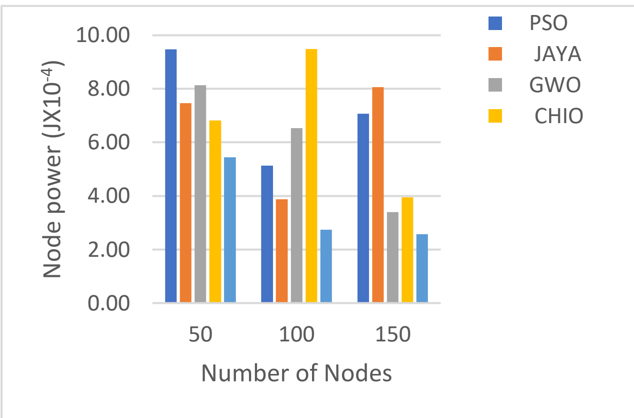

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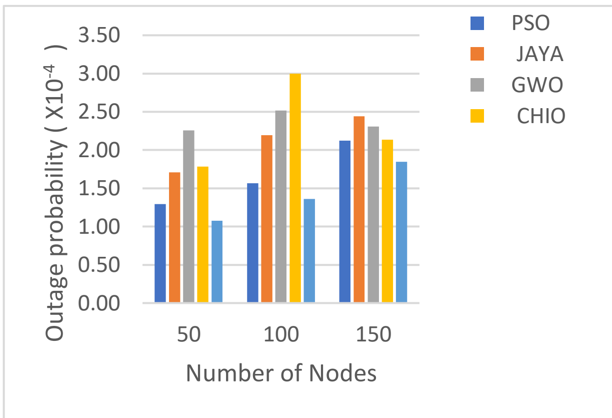

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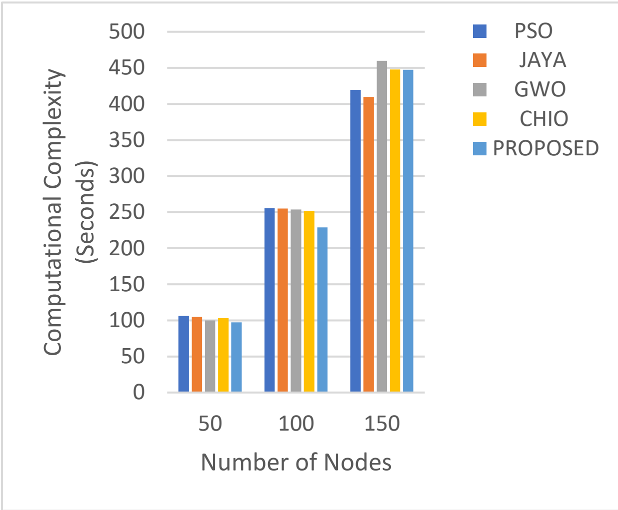


(g)

Fig. 3.9 Performance analysis of the proposed algorithm (Dataset-3) in terms of "(a) throughput, (b) time delay, (c) data rate, (d) energy consumption, (e) node power, (f) outage probability, and (g) Computational Complexity"

Comparative analysis of various parameters on the proposed algorithm (Dataset-1)

	Data Rate	Energy Cons.	Throughput	OutP	Sim.T.
50 nodes	4.8 Mbps	4.0×10^{-4} J	0.76 b/s/Hz	0.177	45.82
100 nodes	9.6 Mbps	3.6×10^{-4} J	0.63 b/s/Hz	0.161	175.89
150 nodes	14.4 Mbps	2.9×10^{-4} J	0.72 b/s/Hz	0.133	435.82

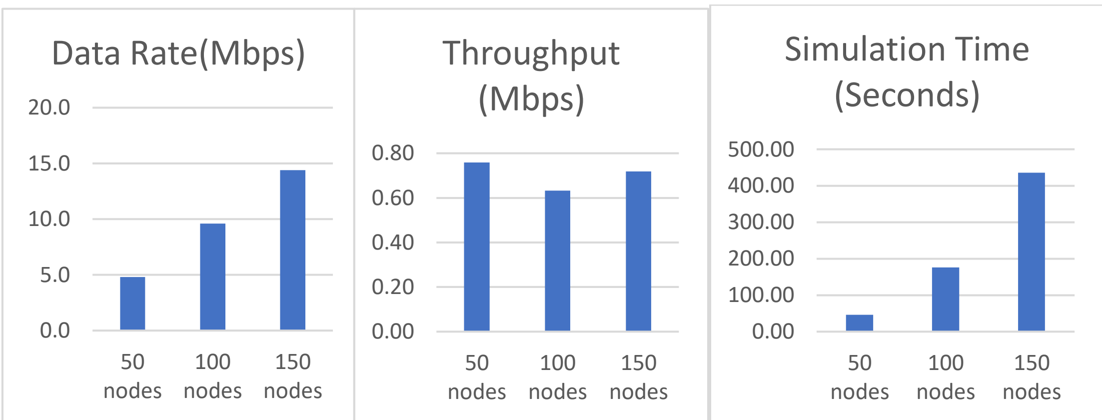


Fig. 3.10 Comparative analysis of the proposed algorithm in terms of (a) Data rate (b)Throughput and (c) Simulation Time

3.7 Conclusion

Implemented in this study is a cognitive routing protocol within IoT, utilizing the suggested SR-CHGWO for efficient Health Information transmission. The selection of cluster heads, crucial for effective data transmission, is conducted with the proposed SR-CHGWO, considering multi-objective constraints such as "distance, energy, throughput, data rate, outage probability, and delay." These constraints are instrumental in ensuring data transmission in the IoMT network without delays or interference. Evaluation of the proposed SR-CHGWO confirms its superiority, exhibiting enhancements of 42.50%, 27.18%, 33.16%, and 20.30% compared to PSO, JA, GWO, and CHIO, respectively, in node power analysis. This underscores the effectiveness of Health Information transmission through cognitive routing in IoT, as facilitated by the proposed SR-CHGWO. Additionally, simulation results highlight the superior computational complexity of the proposed algorithm when compared to traditional optimization methods.

CHAPTER 4
ENERGY HARVESTING BASED CRSN

Due to the rapid growth in the number of interconnected IoT devices worldwide, data transmission capability of the IoT sensor nodes alternately can be termed as wireless sensor nodes suffer from spectrum congestion problems due to limited ISM bandwidth. To address the spectrum crunch issues a new technology needs to be integrated which leads to a new technology named as cognitive radio based IoT. CR node in IoT continuously monitors the surrounding environment to sense and occupy the available vacant channel for the transmission of the data. Due this CR nodes poses energy efficiency issues which reduces the lifetime of the network drastically. In recent research history Energy Harvesting methods took a drastic advancement in its technological design methodologies with greater amount energy conversion efficiency. In this research work we aim to integrate EH methods with CRSN to prolong the lifetime of the network to transmit the large medical data collected by IoMT devices.

4.1 Introduction

Energy harvesting emerges as a dominating technology in the context of future generation wireless networks, such as Internet-of-Things (IoT) and other wireless networks. These networks face challenges associated with the limited size of connected devices, which necessitate fulfilling their energy requirements through harvesting techniques, especially via Radio Frequency (RF) links, to overcome constraints imposed by restricted battery storage capabilities [96]. Thus, the development of wireless networks incorporates energy transmission antennas or nodes that serve the dual purpose of transmitting both data and energy, playing a crucial role in the evolution of communication systems. This concept is embodied in the Hybrid Base Station (HBS), where nodes possess the capability of both data and energy transmission, as well as reception [97, 98]. The merits of energy harvesting approaches are particularly evident in environments characterized by substantial interference. Cognitive Radio (CR) networks offer valuable solutions by facilitating the co-existence of Secondary Users (SUs) and Primary Users (PUs) within the RF spectrum [99]. Commonly employed paradigms in CR networks involve ensuring that SU networks can transmit data concurrently with PUs while adhering to specified PU interference constraints [100].

The integration of recently developed technologies, such as CR and energy harvesting, leads to improved use of available RF sources, encompassing both RF-transmitted energy and the RF spectrum [101]. Advances in pattern recognition and multimedia-based medical technologies contribute significantly to daily life through innovations like smart hospitals, smart medical facilities, and smart clinics, particularly in the realms of health monitoring and disease diagnosis. However, communication networks supporting these innovations encounter numerous challenges. The incorporation of CR networks, guided by emerging technologies, facilitates the resolution of these challenges by forming clusters to track node information [102].

CR's adaptability within wireless technologies allows for dynamic spectrum access by modifying optimal parameters based on the working environment [103]. It supports various technologies to initialize wireless adaptability, emphasizing adaptability and reconfigurability's characteristic features [104]. CR functionality addresses the transmitter's requirements in terms of agility and flexibility, enabling adjustments to radio parameters to achieve spectrum goals, sensing needs, and environmental state considerations [105]. Sensing becomes crucial for devices to assess transmitter parameters, considering RF environment knowledge. Networks with sufficient capacity are essential for learning and adapting patterns according to working nature, environmental conditions, and improving pre-coded algorithms' performance through a learning approach [106]. CR facilitates interactions between two non-CR platforms independently, fostering interoperability across diverse platforms without centralized control. Given the evolving demands in spectrum usage, spectrum policymakers find appropriate solutions to ensure spectrum security [107].

Simulation research indicates that various licensed users share the spectrum during idle periods, prompting the exploration of unlicensed user access to these idle spectrums within licensed bands [108]. These approaches exhibit dynamic behaviors in spectrum access, introducing flexibility to the network [109]. Multiple access methods can be deployed in regions where higher-level transmissions occur within the same band. An essential challenge in this context is energy harvesting, which can significantly impact network stability and lifetime [110]. Scalability becomes a critical consideration as the network accumulates a substantial number of nodes [111].

In Cognitive Radio (CR) networks, enhancing network performance requires careful monitoring of broadcast communications [112]. This monitoring process can have adverse effects, such as insufficient energy supply to sustain operational parameters across all nodes. In CR networks, energy harvesting, and scalability are often recognized as highly challenging aspects, necessitating the design of an improved Cognitive Radio Sensor Network (CRSN) routing protocol that incorporates energy harvesting through optimization algorithms.

Below are the key contributions of the energy harvesting-based Cognitive Radio Sensor Network (CRSN) that has been developed.

- Implementing an optimized energy harvesting scheme with a hybrid strategy to ensure seamless medical data transmission without interference or information loss on IoMT devices.
- Designing a hybrid heuristic technique, HCSEHO, for efficient energy harvesting in CR networks by selecting the optimal cluster head from source to destination nodes, ensuring effective medical data transmission.
- Assessing the effectiveness of the developed Cognitive Radio Sensor Network (CRSN) in the Internet of Medical Things (IoMT) framework through comparison with conventional approaches across various objectives.

In summary, the study focuses on optimizing energy harvesting in IoMT devices, designing a hybrid heuristic technique for efficient energy harvesting in Cognitive Radio Sensor Networks, and evaluating the effectiveness of the developed approach compared to conventional methods.

4.2 Problem statement

Recently, the CR networks have focused on leveraging scattered data related to spectrum allocation, routing, dynamic spectrum access, and spectrum sharing. However, the CR network lacks emphasis on energy consumption and fails to deliver consistent performance. Therefore, the CSRN has been developed to offer effective routing in wireless transmission. The Multi Objective Ant Colony Optimization [23] method is employed to enhance residual energy and prolong network lifespan. However, it lacks superior performance in evaluating energy properties and exhibits increased complexity during the execution of jamming assaults. Unconstrained PSO [94] prioritizes optimal energy transmission power and low system outage performance, however it does not provide sufficient attention to route selection and power distribution in underlay nodes.

The EAQ-AODV [113] method is used to improve network energy and minimize data packet transmission time. Nevertheless, this technique increases energy consumption for battery-operated devices and reduces per-node capacity utilization. For various destination nodes, the TCEM algorithm [114] shows to be a workable and efficient way of achieving great energy productivity in the overall network. Nevertheless, the network forfeits generality as a result of the variance in power transmission throughout each node. The problem of outage reduction is tackled by the Fully EH-enabled multi-hop CR Network (CRN) [115], which considers relay power, source, and relay harvesting time. However, it fails to take into consideration the issue of outage secrecy minimization when the number of eavesdroppers rises. ERCR [116] selects a route with a low amount of energy requiring a very small number of forwarding nodes. As a result, it is restricted while using the medium access method to access the specific wireless channel. Improved performance in terms of throughput, packet delivery ratio, and end-to-end packet latency is offered by HyMPRo [117]. However, it does not focus on the model's multi-path communication to increase its flexibility. The dynamic spectrum and energy-related problems are resolved by EACRP [118]. However, difficulties arise because of the frequent re-clumping caused by PU actions.

Sensor nodes operate in an unattended environment and hence sensor nodes become useless when their battery is depleted. It is important to note that although there is a lot of radio frequency (RF) energy available everywhere, it has a low power density. Energy harvesting allows electronics to operate where there's no conventional power source, eliminating the need to run wires or make frequent visits to replace batteries.

4.3. Energy Harvesting based CR Routing

4.3.1 Proposed model and its description

Wireless energy harvesting is emerging as a technology allowing devices to integrate with necessary hardware to extract energy from various sources such as radio frequencies, thermoelectric, and solar devices. Recently, researchers have shown a keen interest in energy harvesting through RF devices in wireless networks. While IoT technology benefits from wireless energy harvesting, the batteries of IoT devices [119] often face challenges of frequent replacement or recharging. Utilizing smart wireless energy harvesting approaches in wireless devices can significantly improve network lifetime compared to traditional battery usage. Cognitive Radio (CR) adds another layer of flexibility by enabling channel switching or assigning Secondary Users (SUs) to utilize licensed frequency bands. This energy harvesting presents a promising solution for conventional wireless communication devices.

In a CR network, Spectrum Users (SUs) detect spectrum holes through spectrum sensing, efficiently transmitting information and energy during the specified phase. However, during PU activation in the transmission phase, SUs are restricted from interaction to enhance service quality for licensed PUs and reduce interference effects.

In an energy harvesting-based Cognitive Radio (CR) network, mobile devices, often referred to as Secondary Users (SU), are equipped with the capability to harvest energy from

Radio Frequency (RF) signals. These RF signals can originate from either the Primary User (PU) transmitter or the base station within the network. The goal is to make optimal use of the PU's signal, and this is achieved through the transmission of both information and harvested energy to both PU and SU.

The process involves the efficient utilization of the PU's signal, where information and energy harvesting occur simultaneously. The information is transmitted using the information power, while wireless transfer methods are employed to convey both information and harvested energy to both the PU and SU within the network. This integration of energy harvesting with CR technology enables mobile devices to sustain their operations by harnessing energy from the surrounding RF signals, thereby contributing to the overall efficiency and sustainability of the CR network.

A new energy harvesting-based Cognitive Radio Sensor Network (CRSN) is developed for medical data transmission, as depicted in Fig. 4.1. The routing in this CRSN is specifically designed to transmit medical data, focusing on enhancing energy harvesting and minimizing delay in the network's data transmission performance. Addressing issues in medical data transmission over Cognitive Radio Sensor Networks (CRSN), a heuristic strategy named HCSEHO is developed. This strategy aims to enhance efficacy by selecting the best cluster head among all nodes during data transmission. However, the cluster head selection process may lead to reduced energy, potentially causing alive nodes to be mistakenly considered in a dead state. To resolve this, the proposed model tackles the alive nodes problem by initially setting the harvesting energy to 0.2 for data transmission. When the normalized energy falls below a specified threshold, the node's energy is replenished from the harvesting energy, effectively recovering nodes from a potentially erroneous dead state and facilitating efficient data transmission. Therefore, the routing protocol devised for Cognitive Radio Sensor Networks (CRSN) contributes to improved energy harvesting and extended network lifespan during the transmission of medical data, ensuring minimal delay. Subsequently, a multi-objective function is executed, considering constraints such as distance, energy harvesting, throughput, hop count, data rate, power, outage probability, and delay, with the aim of enhancing overall performance.

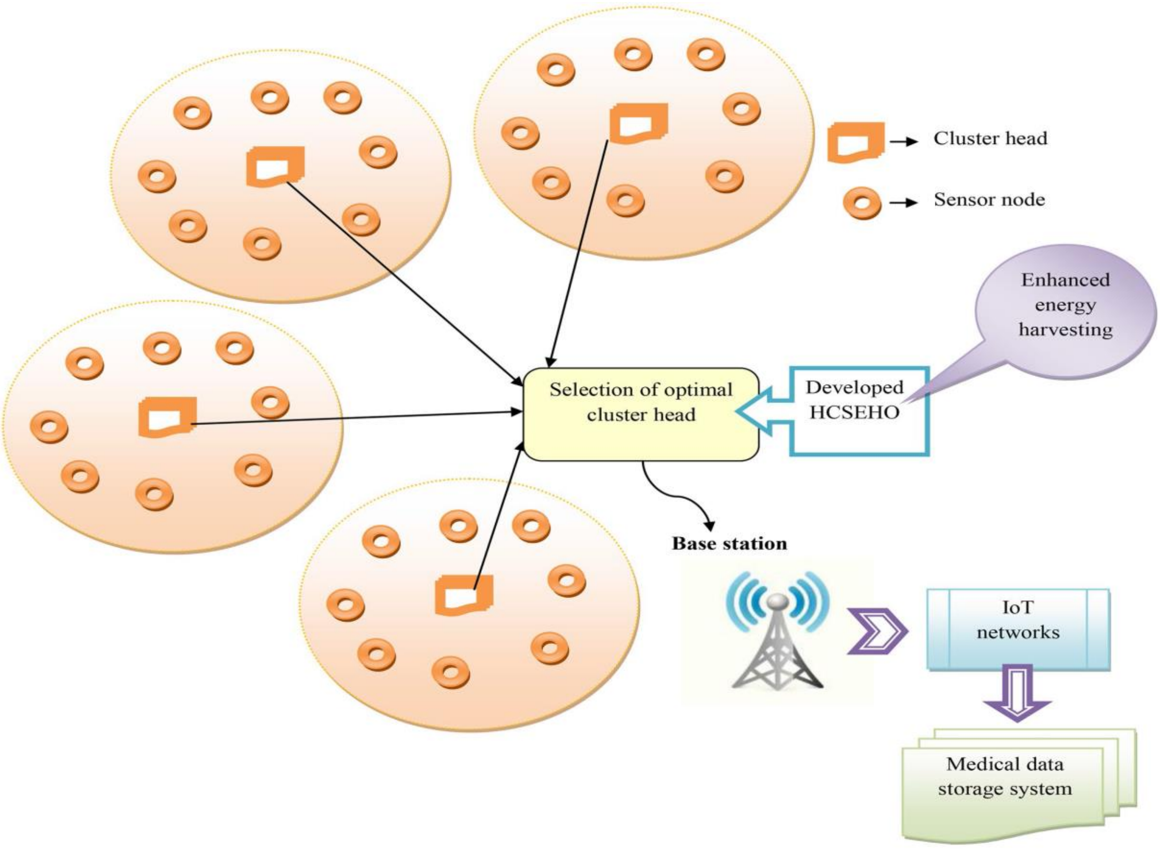


Fig. 4.1 Diagrammatic representation of designed EH-CRSN framework

4.3.2 Energy Harvesting model

The Energy Harvesting (EH) model entails a fixed Single User (SU) source equipped with multiple antennas (M_t) associated with a Primary User (PU) pair [120]. The Hybrid Base Station (HBS) is responsible for energy transmission via antenna 'f' and acquiring data from the SU with antenna 'e'. Additionally, the SU adopts a spectrum-sharing paradigm for energy harvesting, ensuring that the total power for both energy and data transmissions remains below the achievable interference limit R_Q of the PU. The SU source operates with a limited battery storage capacity, necessitating the harvesting of sufficient energy from both the PU and Hybrid BS networks to facilitate the data transmission. The energy $\hat{R}_{ES}$, established at the SU's starting point in the preceding time slot before data transmission, is computed using Eq, (4.1).

$$\hat{R}_{ES} = \upsilon(Q_{PT}\|f_{TS}\|^2 + Q_E\|i_{ES}\|^2) \quad (4.1)$$

$\|\cdot\|$ indicates the Frobenius norm of the vectors.

f_{XY}, i_{XY} are the channel along the two nodes X and Y both PU and SU respectively.

Q_{PT} indicates PU transmitter power and Q_E indicates the available harvesting energy over the hybrid BS.

The efficiency of harvesting energy is represented by the coefficient υ at time slot T ($0 \leq \upsilon \leq 1$). If the total energy of a node is above a defined threshold $\hat{R}_E$, then SU will perform data transmission. If $\hat{R}_{ES} > \hat{R}_E$ then SU will be allowed for data transmissions over the network. If $\hat{R}_{ES} < \hat{R}_E$ then the system aborts the SU data transmission. Here a"piece-linear energy harvesting model" is incorporated due to its simplicity.

Further it is assumed that the Hybrid BS (HBS) is regarded as lacking current information after the energy harvesting from Secondary Users (SU) to provide ample energy for data communication. If $\hat{R}_{ES} > \hat{R}_E$, the SU provides enough power for data transmission towards the HBS receiving antenna f with power Q_T by considering the constraint R_Q .Therefore, the deduction is drawn that the influence of Secondary User (SU) transmission results from two types of interference signals affecting the Hybrid Base Station (HBS). The first type is the "Co-Channel Interference (CCI)" signal impacting the transmission from the Primary User (PU) to 'e'. The second cause is self-interference affecting the transmitting antenna 'f' from the HBS. To mitigate this, approaches like "Self-Interference Cancellation (SIC)" can be employed. The energy harvesting model, considering a single SU source, is illustrated in Fig. 4.2.

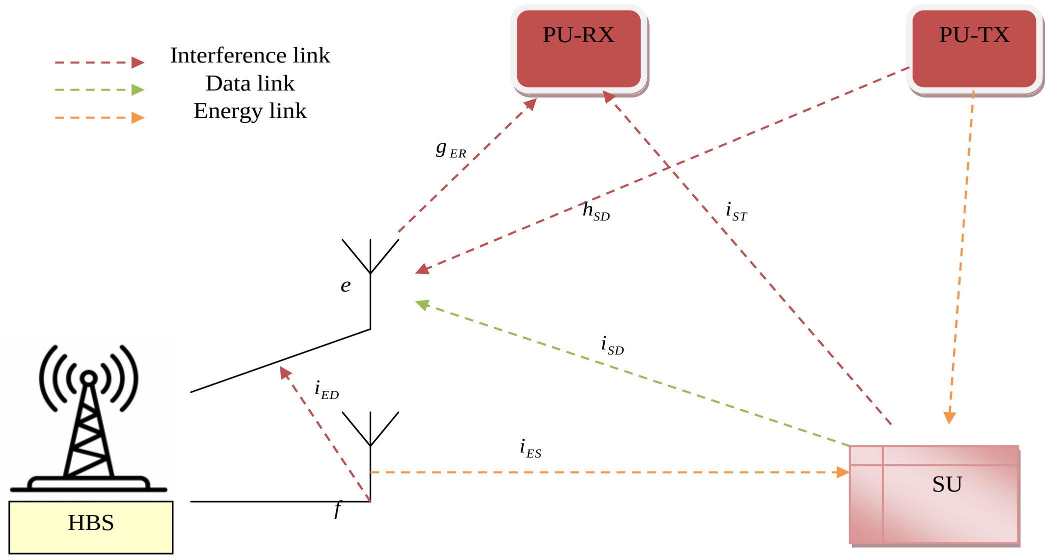


Fig. 4.2 Designed energy harvesting CRSN framework with a single SU source

4.4. Development of novel HCSEHO for optimal CR routing

4.4.1 Cluster Head Optimization

A key strategy for increasing a wireless communication network's lifespan is clustering. This entails clustering a collection of sensor nodes and choosing a cluster head by applying the implemented HCSEHO while taking into account all cluster heads that are accessible. In order to facilitate data or message sharing across nodes, each cluster is given a time slot during cluster creation, which is determined by the cluster head. Cluster heads are essential to gathering information from every node in their clusters. The cluster head aggregates data and sends medical data to the base station when all nodes have collected the required information. After that, until every node is processed, data transmission and re-clustering occur in repeating cycles. The cluster unites with the closest clusters if its size drops below a certain threshold, suggesting that it is quite tiny. As a result of this merging process, there are fewer active nodes, fewer cycles, and ultimately fewer clusters overall. The number of nodes in the physical environment falls in tandem with a drop in the volume of information.

Objective Function description

Using the developed Hybrid CSO-EHO algorithm, the proposed EH-based CRSN routing architecture in IoMT selects the optimum cluster head in order to achieve the multi-objective function with "the distance, energy, throughput, hop count, probability of outage and latency." This expression refers to the invented routing protocol's objective function, as seen in Equation (4.2).

$$B_{ob-f} = \underset{\{CH_r^{op}\}}{argmin}(Ff_5) \tag{4.2}$$

For the medical data transfer, the ideal cluster head is chosen and denoted by CH_r^{op}. The following equations may be derived to obtain the objective Ff_5.

$$Ff_1 = Pp * DIs + \left((1 - Pp) * \left(\frac{1}{Q_E}\right)\right) \tag{4.3}$$

$$Ff_2 = Qq * Ff_1 + \left((1 - Qq) * DEl\right) \tag{4.4}$$

$$Ff_3 = Rr * Ff_2 + \left((1 - Rr) * (HOc)\right) \tag{4.5}$$

$$Ff_4 = Ss * Ff_3 + (1 - Ss) * (THr) \tag{4.6}$$

$$Ff_5 = Tt * Ff_4 + (1 - Tt) * \left(\frac{1}{OPr}()\right) \tag{4.7}$$

In this case, the values of alpha (Pp), beta (Qq), gamma (Rr), omega (Ss) and epsilon(Tt) are set at 0.2, 0.1, and 0.2 respectively.

4.4.2 Proposed HCSEHO for CR routing

The proposed Cognitive Radio (CR) networks in the Internet of Things (IoT) employ best CH selection through the proposed Hybrid-CSEHO to enhance the harvesting energy capability of the HBS antenna and facilitate optimum medical data transmission. The chosen EHO [121] is selected for its proficiency in addressing a variety of optimization problems, including continuous optimization, combinatorial optimization, constrained optimization, and multi-objective optimization, along with its capability to handle diverse engineering challenges. However, EHO tends to be inefficient in theoretical analysis interpretation and exhibits lower performance in solving constrained optimization problems.

To overcome this, CSO [122] algorithm is combined with EHO to create Hybrid CS-EH Optimization algorithm to tackle with the conventional problems. In Hybrid CS-EHO, the final position of the solution is obtained by using the first position xi_1 obtained from CSO algorithm and the second position xi_2 obtained from EHO algorithm by using Eq. 4.8

$$xi^{fin} = mean(xi_1, xi_2) + \frac{std(xi_1, xi_2)}{2} \tag{4.8}$$

Here, the terms $std(xi_1, xi_2)$ and $mean(xi_1, xi_2)$ will indicate the standard deviation and mean and of the two positions vectors. The major parameters involved in the development of CSO [122] algorithm as summarized as follows

Generally, each and every cuckoo has the ability to lay only one egg at a time, and this egg is randomly deposited into other nests. Subsequently, only the nests that contain superior-quality eggs manage to survive to progress to the next generations. The availability rate of host nests is predetermined, and the host can potentially create an alien egg based on the probability denoted as $Pi_{ai} \in [0,1]$. This probability fraction, Pi_{ai} is considered for a certain number of nests ni and is used to modify the newly generated nests. The process involves generating new solutions represented as $xi^{(ti+1)}$ according to Eq. (4.9), wherein a Levy flight is also incorporated.

$$xi_{ii}^{(ti+1)} = xi_{ii}^{(ti)} + \alpha \oplus Lev(\lambda) \tag{4.9}$$

The term $\alpha > 0$ represents step size. The product $\oplus$ signifies entry-wise multiplications, and Levy flights guarantee a random walk. The arbitrary steps in the random walk are derived from the levy distribution, as illustrated in Eq. (4.10).

$$Lev \approx ui = ti^{-\lambda}, (1 < \lambda \leq 3) \tag{4.10}$$

Clan-updating operator: Drawing inspiration from the inherent behavior of elephants, every elephant within the clan adheres to the guidance provided by the matriarch. Consequently, the position of each elephant is determined using Eq. (4.15).

$$xi_{New,Ci,ki} = xi_{Ci,ki} + \alpha \times \left(Pi_{bt,Ci} - Pi_{Ci,ki}\right) \times Ri \tag{4.11}$$

$Pi_{Ci,ki}$ - old position

$xi_{New,Ci,ki}$ - updated position of elephant ki among clan Ci.

$Pi_{bt,Ci}$ - position matriarch position (best elephant among the clan)

Ri - random variable in the interval $[0,1]$ and α is a random scaling factor

The matriarch position (optimal elephant) in the clan is determined by Eq. (4.12).

$$xi_{New,Ci,ki} = \beta \times xi_{Ctr,Ci} \tag{4.12}$$

The central position of the elephant in the clan Ci is indicated by $xi_{Ctr,Ci}$ and it can computed by using Eq. (4.13).

$$xi_{Ctr,Ci,li} = \frac{1}{Ni_{Ci}} \times \sum_{ki=1}^{Ni_C} xi_{Ci,ki,li} \tag{4.13}$$

Ni_{Ci} - Total number of elephants

$xi_{Ci,ki,li}$ - Pposition of the elephant at li^{th} dimension

The worst fitness among the elephants is expressed as in Eq. (4.18).

$$xi_{wst,Ci} = xi(ximin_{max} \times Ri_1)_{min} \tag{4.14}$$

R_{i1} lies in the interval $[0,1]$.

xi_{max} and xi_{min} are upper bound and lower bounds

The pseudo-code of the developed HCSEHO is shown in Algorithm 4.1.

Algorithm 4.1: **HCSEHO**

Input: Optimal cluster head CH_r^{op}

Output: Optimal solution

Initialize Elephant and cuckoo populations

While (till the termination criteria) do

  Fitness calculation for all solutions in the population

    For each solution

      Update the 1st position using Eq. (4.7)

      Update the 2nd position using Eq. (4.12)

      Update the final position using Eq. (4.1)

    End for

  Position-based fitness estimation of all solutions.

End while

Return the best Solution

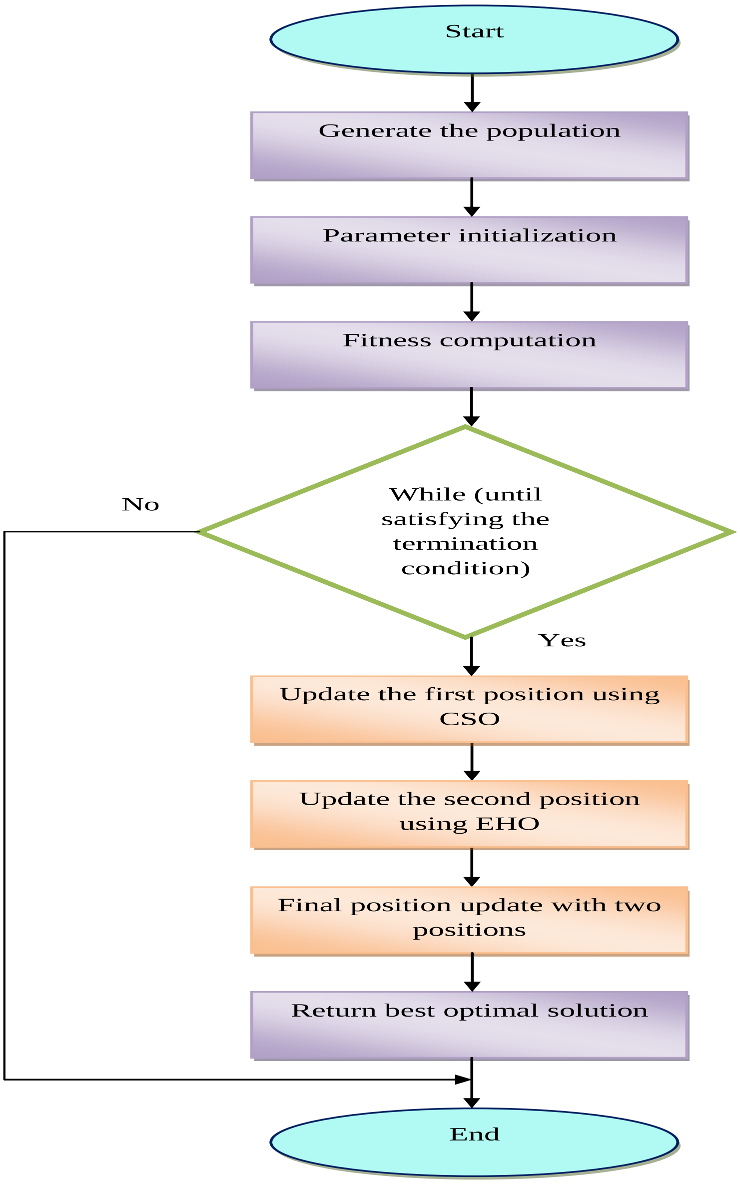


Fig.4.3. Flowchart of Proposed HCSEHO

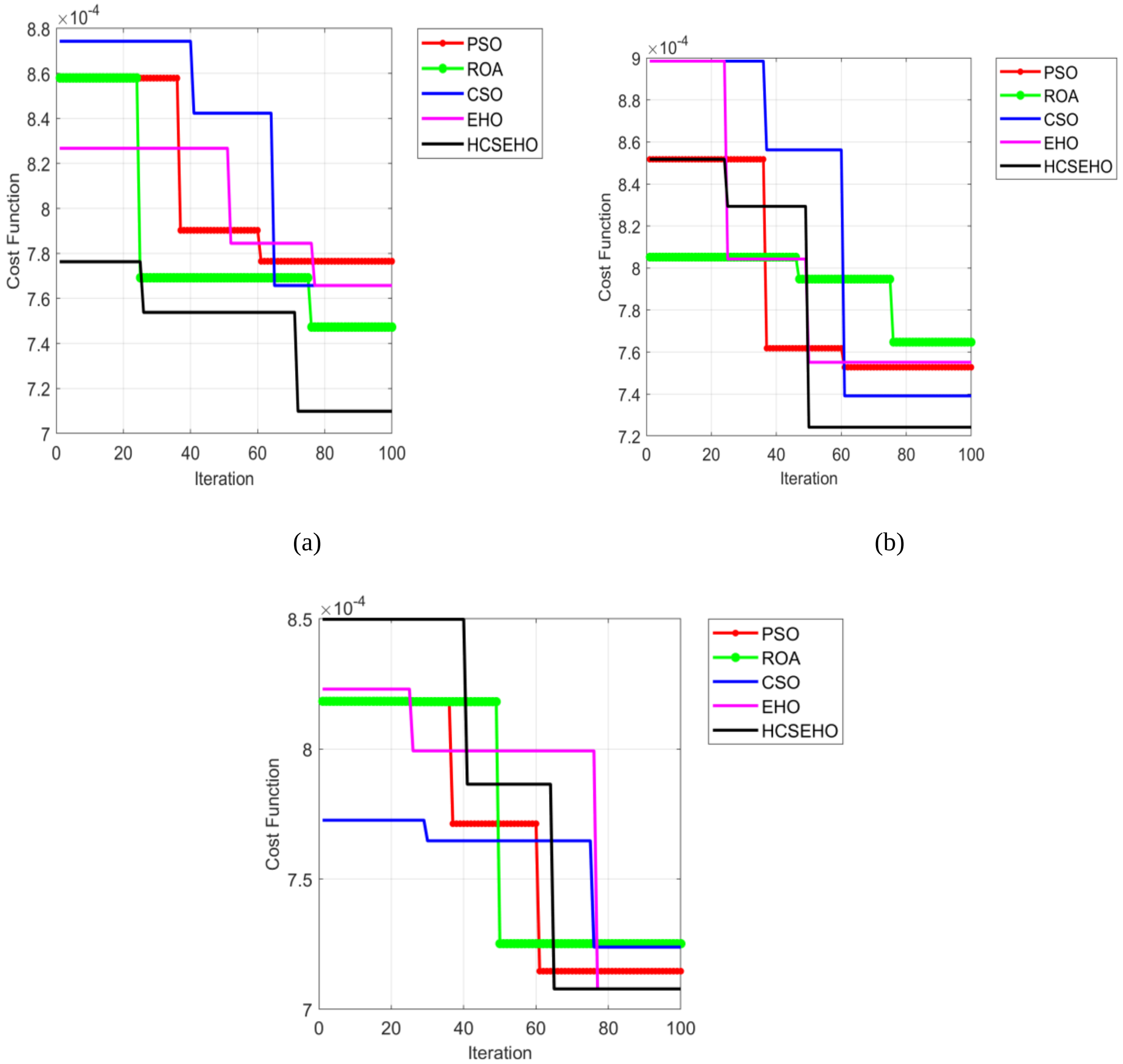
4.5. Results and discussions

4.5.1 Simulation Setup

The EH-CRSN framework for health data transmission, designed with Hybrid CS)-EHO, was simulated using MATLAB 2020b and subjected to various analyses. The simulation involved a maximum of 100 iterations with a populations size of 10. Additionally, a comparative assessment was conducted between the proposed Hybrid CSO-EHO algorithm and conventional algorithms, including Particle Swarm Optimization (PSO) [19], Rider Optimization (ROA) [123], CSO [122] and EHO [121]. This comparison aimed to assess the scalability of the model to ensuring secure transmission of medical data .

4.5.2 Cost function evaluation

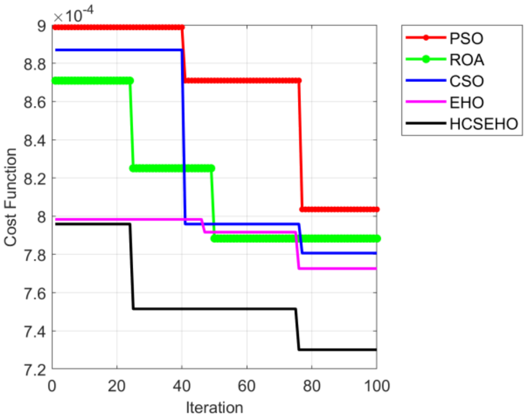
In Figures 4.4, 4.5, and 4.6, three distinct medical datasets are employed to analyze the cost function within the designed energy harvesting-based Cognitive Radio Sensor Network (CRSN) framework for medical data transmission. This analysis is conducted using the developed Hybrid Cuckoo Search Elephant Herding Optimization (HCSEHO) while varying the number of nodes. The results demonstrate that the designed energy harvesting-based CRSN framework for medical data transmission exhibits improved performance in transmitting medical data over the CRSN without any delays, accompanied by enhanced energy harvesting capabilities.



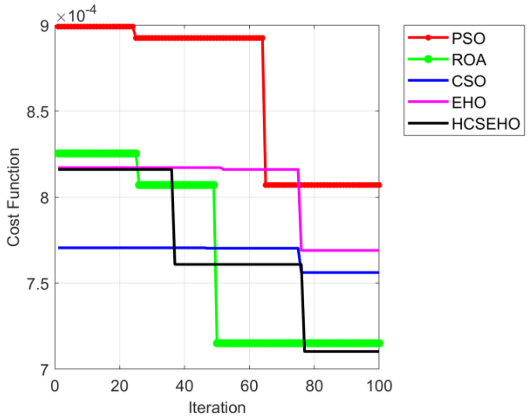
(a) (b)

(c)

Fig.4.4. Validation of EH-CRSN framework (Dataset-1) under 50, 100 and 150 nodes



(a)



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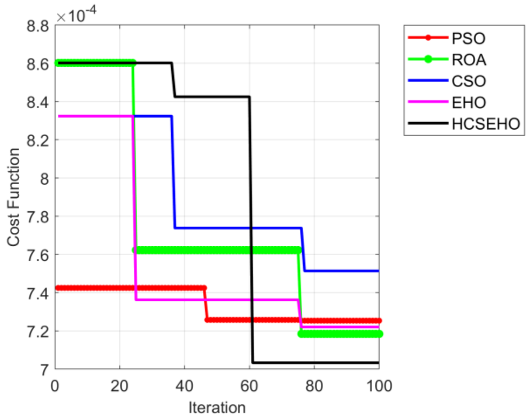
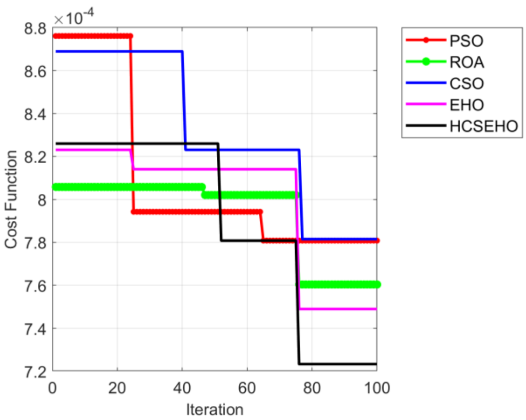
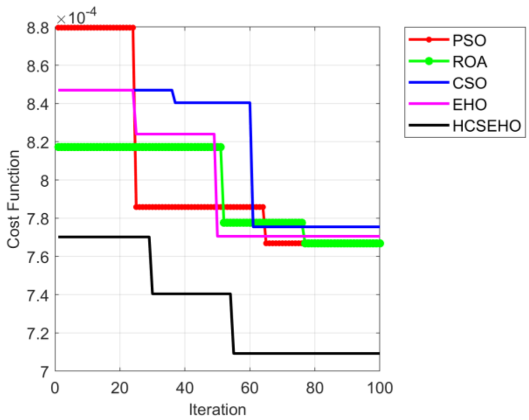


(c)

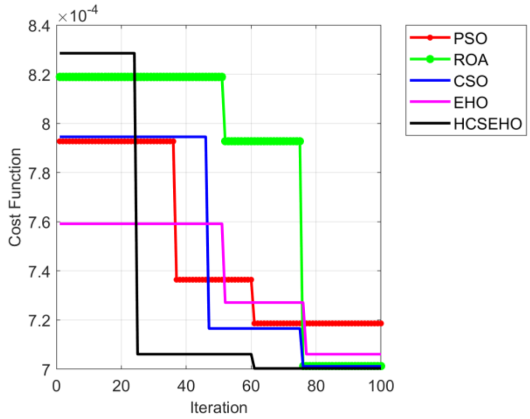
Fig.4.5. Validation of EH-CRSN framework (Dataset-2) under 50, 100 and 150 nodes



(a)



(b)



(c)

Fig.4.6 Validation of EH-CRSN framework(Dataset-3) 50, 100 and 150 nodes

4.5.3 Performance Analysis

4.5.3.1 Throughput Aanalysis

The analysis evaluates the throughput of the energy harvesting-based Cognitive Radio Sensor Network (CRSN) framework for medical data transmission using various heuristic algorithms, as illustrated in Fig. 4.7. The developed HCSEFO demonstrates superior throughput performance, surpassing PSO, ROA, CSO, and EHO by 13.51%, 17.60%, 16.12%, and 18.91%, respectively. This substantiates the model's superiority in terms of throughput.

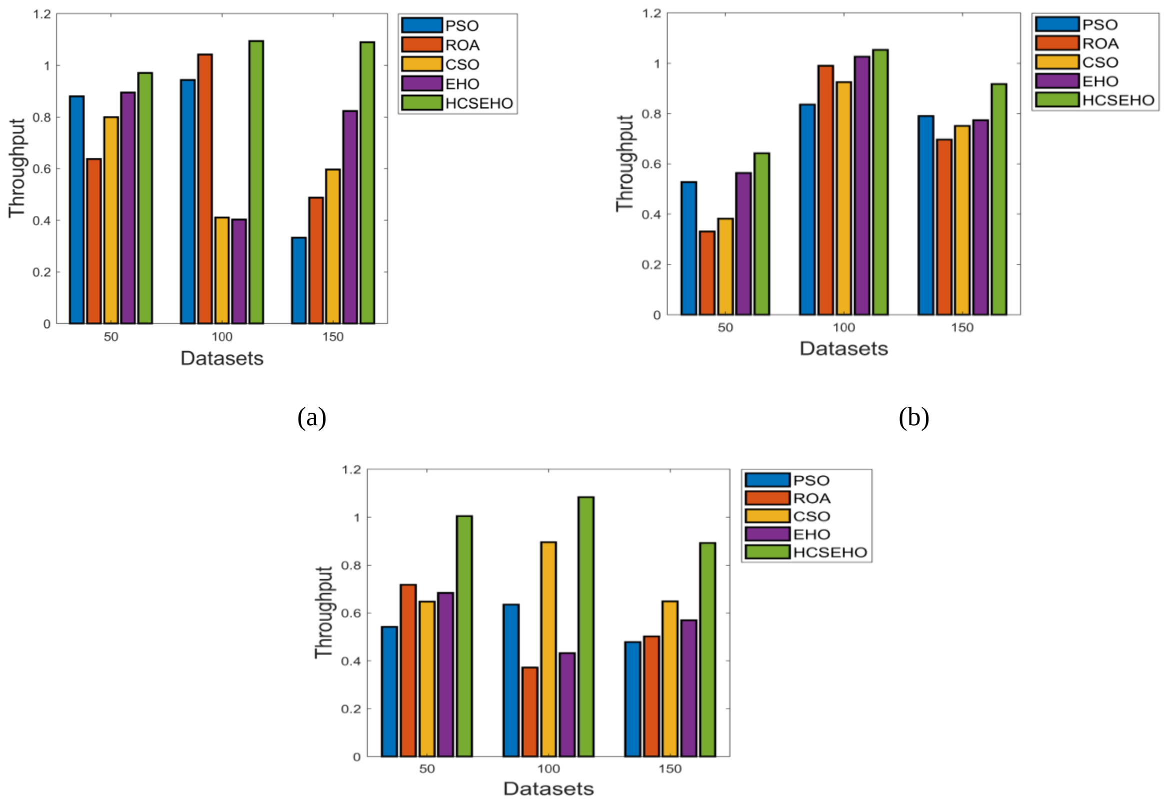


Fig.4.7 Throughput analysis of EH-CRSN using “(a) dataset 1, (b) dataset 2 and (c) dataset 3”

4.5.3.2 Hop count analysis

The evaluation considered the hop count to assess the efficiency of the energy harvesting-based Cognitive Radio Sensor Network (CRSN) framework for medical data transmission across various heuristic algorithms, depicted in Fig. 4.8. The developed HCSEHO exhibits superior performance with a minimal hop count, as observed in the analysis compared to other heuristic strategies such as PSO, ROA, CSO, and EHO.

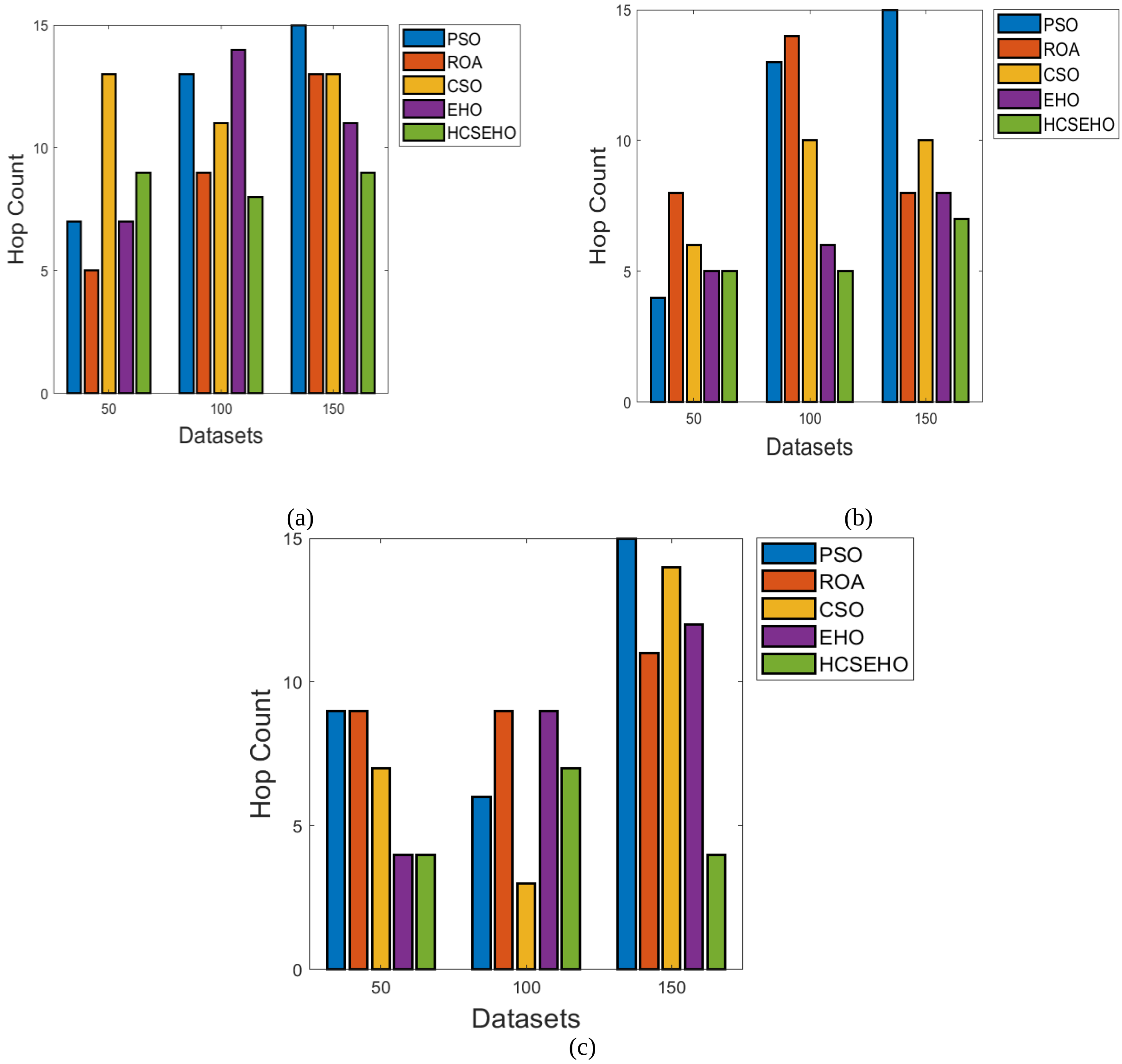
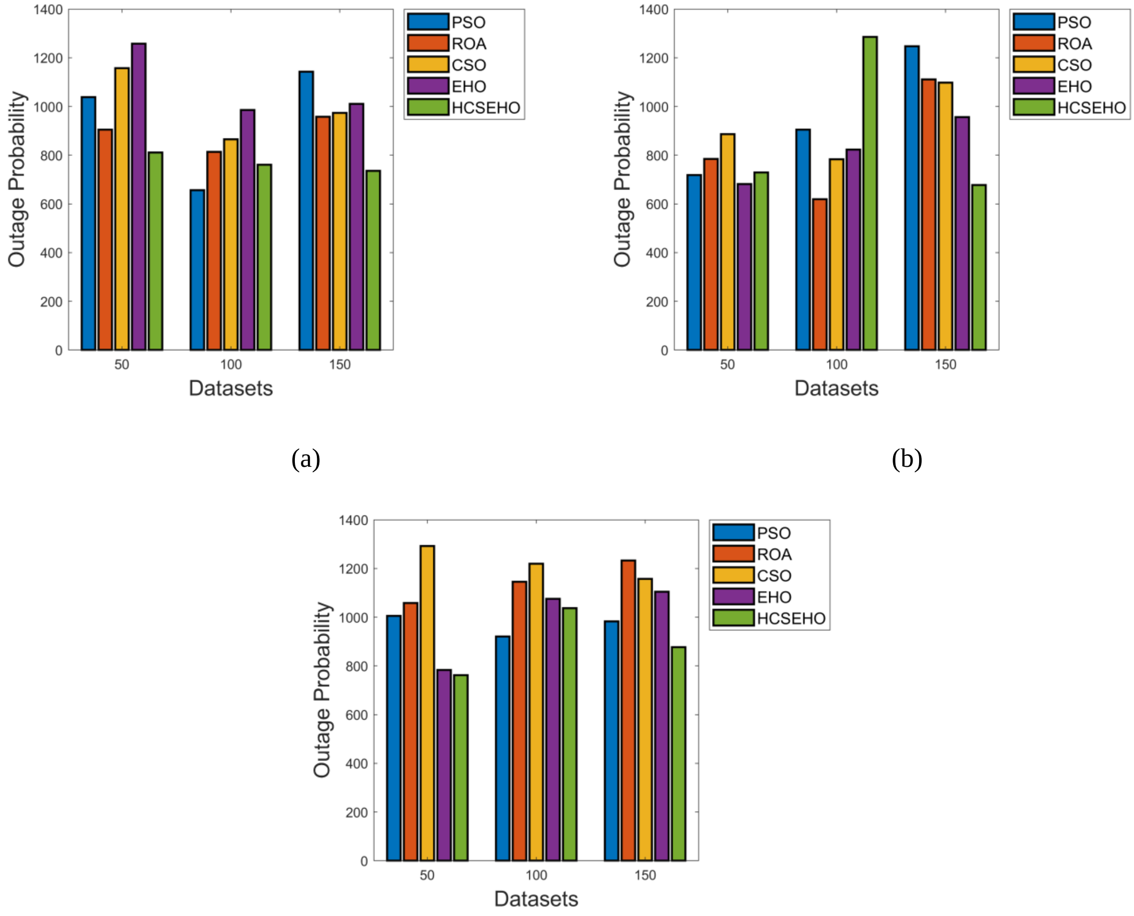


Fig 4.8. Hop count Analysis of EH-CRSN using “(a) dataset 1, (b) dataset 2 and (c) dataset 3”

4.5.3.3 Outage probability analysis

The energy harvesting-based Cognitive Radio Sensor Network (CRSN) framework for medical data transmission underwent an analysis of outage probability across three datasets, illustrated in Fig. 4.9. The outage probability analysis indicates a notable improvement of 11.41%, 24.51%, 17.81%, and 18.71% better than PSO, ROA, CSO, and EHO, respectively.

Consequently, the implemented HCSEHO in the designed energy harvesting-based CRSN framework enhances the efficiency of medical data transmission.



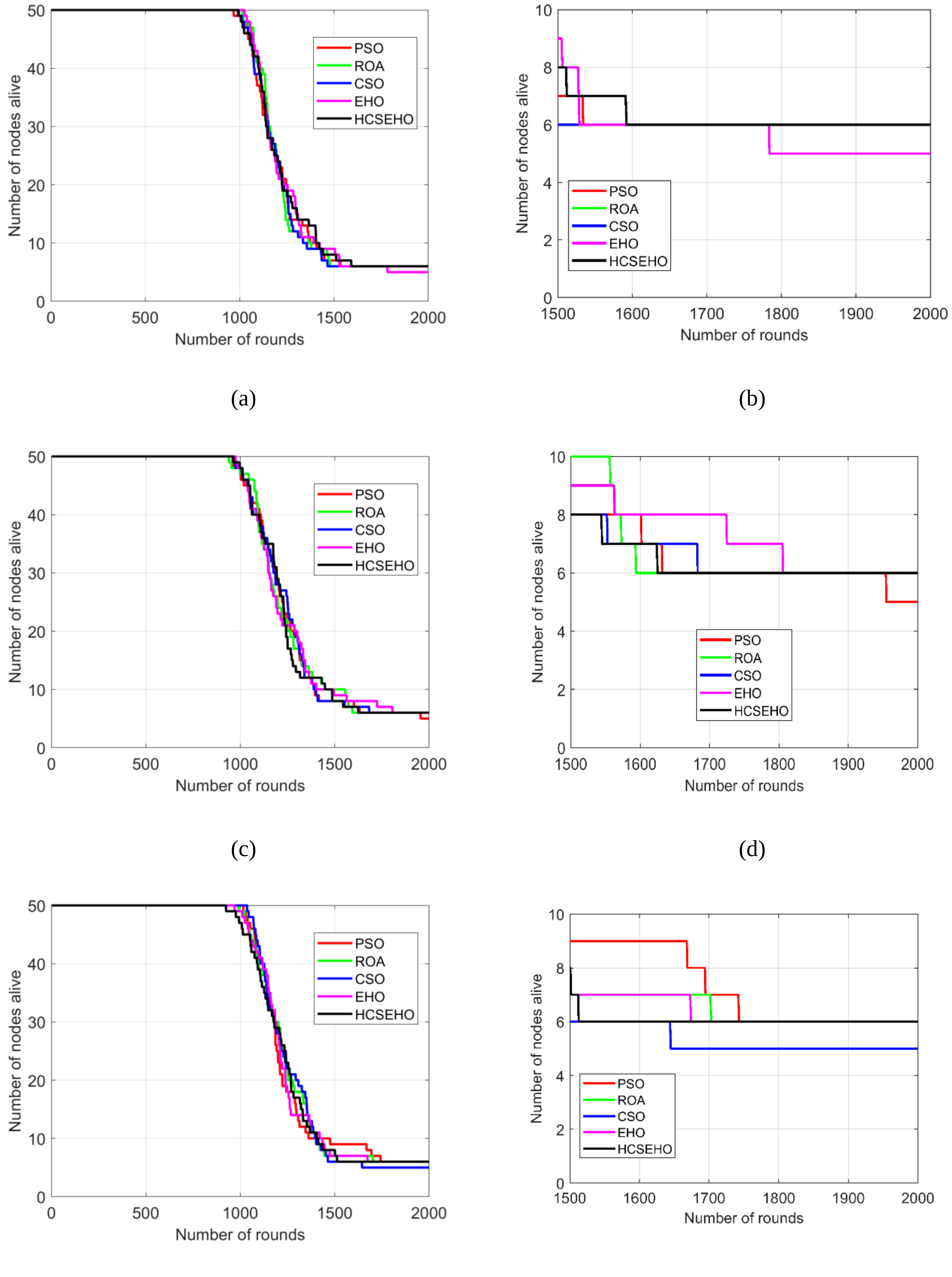
(a) (b)

(c)

Fig 4.9 Outage probability Analysis of EH-CRSN using “(a) dataset 1, (b) dataset 2 and (c) dataset 3”

4.5.3.4 Alive node Analysis

In evaluating the designed energy harvesting-based Cognitive Radio Sensor Network (CRSN) framework for medical data transmission across different heuristic algorithms, Fig. 4.10 illustrates the analysis focused on alive nodes. The analysis shows minimal variation between the performance of the proposed and conventional algorithms, particularly evident in the zoomed graphs for rounds 1990 to 2000. However, the developed framework, aided by the implemented HCSEHO, outperforms existing algorithms, showcasing better overall performance.



(a) (b)

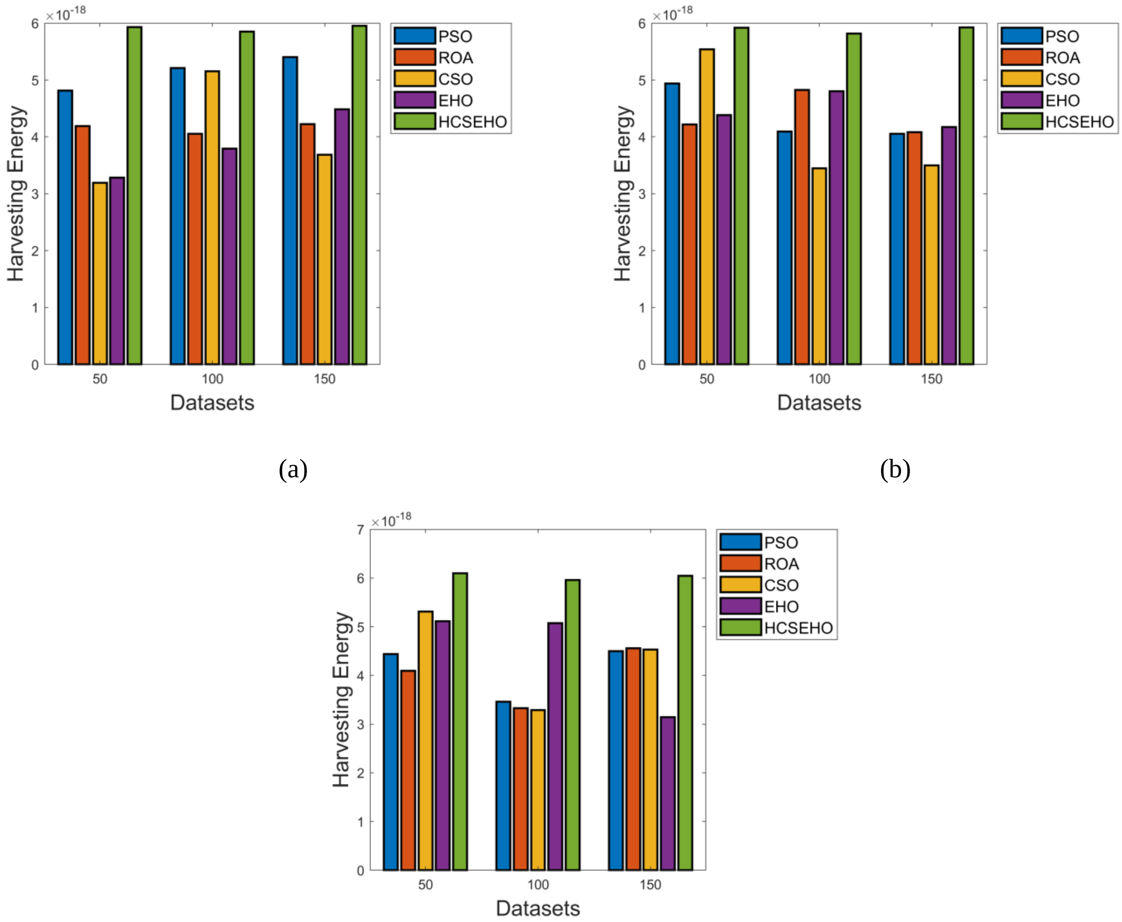
(c) (d)

(e) (f)

Fig.4.10 Alive node analysis of EH-CRSN using "(a) dataset 1, (b) zoom-in of dataset 1, (c) dataset 2, (d) zoom-in of dataset 2, (e) dataset 3 and (f) zoom-in of dataset 3"

4.5.3.5 Harvesting Eenergy analysis

The energy harvesting-based Cognitive Radio Sensor Network (CRSN) framework, tested across three datasets as depicted in Fig. 4.12, exhibits improved efficiency for medical data transmission. This enhancement is attributed to the implemented HCSEHO within the designed framework.

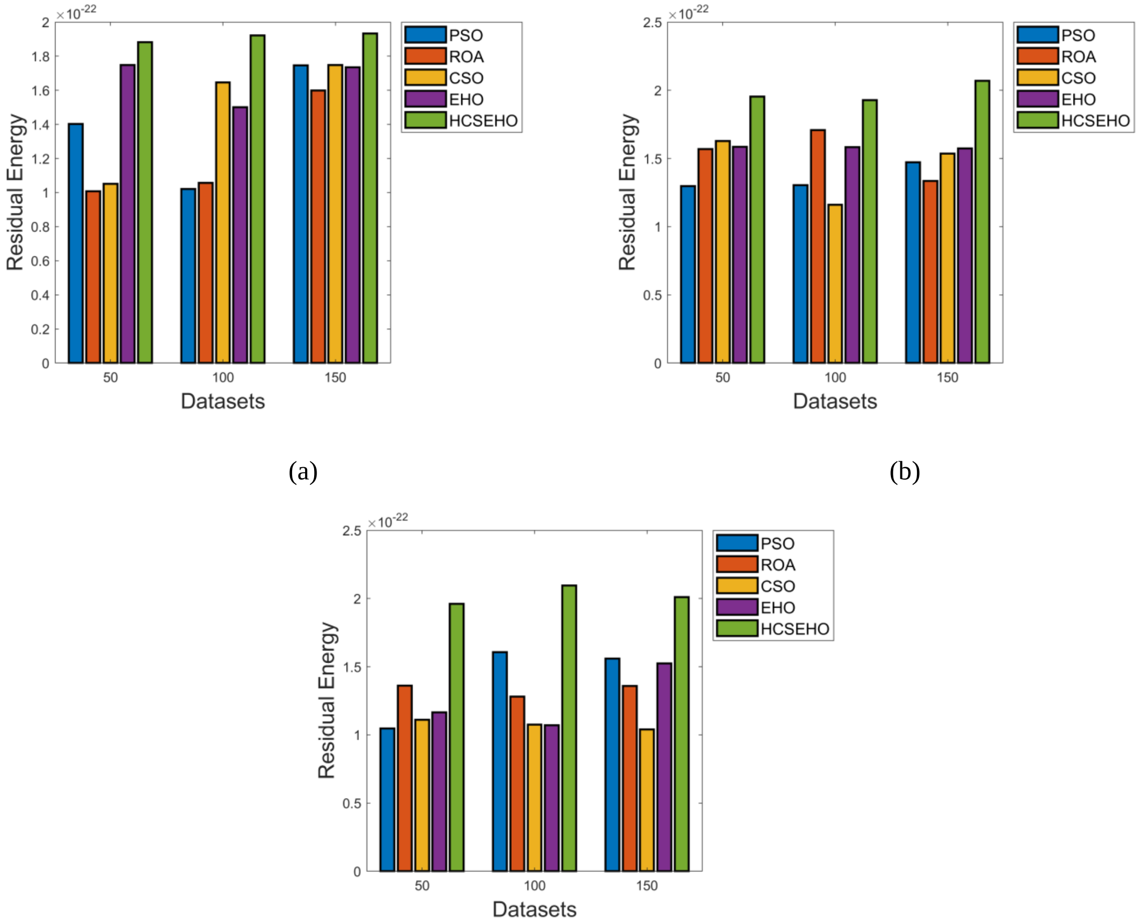


(a) (b) (c)

Fig.4.11 Harvesting Energy analysis of EH CRSN using "(a) dataset 1, (b) dataset 2 and (c) dataset 3"

4.5.3.6 Residual energy analysis

The analysis of the designed energy harvesting-based Cognitive Radio Sensor Network (CRSN) framework, depicted in Fig. 4.13, is conducted based on residual energy across three datasets. The findings reveal that the framework significantly improves the efficiency of medical data transmission, primarily attributed to the support provided by the implemented HCSEHO.



(a)

(b)

(c)

Fig.4.12 Residual Energy analysis of EH CRSN using "(a) dataset 1, (b) dataset 2 and (c) dataset 3"

The efficiency of the designed energy harvesting-based Cognitive Radio Sensor Network (CRSN) framework for medical data transmission is compared with conventional algorithms across three datasets: dataset 1 (Table 4.1), dataset 2 (Table 4.2), and dataset 3 (Table 4.3).

This analysis involves variations in the number of nodes at 50, 100, and 150. Specifically, at 100 nodes, the proposed HCSEHO demonstrates 0.49%, 79.29%, 10.90%, and 44.92% enhanced performance compared to PSO, ROA, CSO, and EHO, respectively, in terms of energy consumption within dataset 1. Additionally, in dataset 2 analysis, the HCSEHO-based medical data transmission achieves 16.16%, 31.86%, 22.22%, and 18.65% improved throughput compared to PSO, ROA, CSO, and EHO, respectively, at 150 nodes. This confirms the superior performance of the proposed model in transmitting medical data over the Cognitive Radio Sensor Network (CRSN) compared to conventional approaches.

TABLE 4.1 DATASET 1 ESTIMATION OF EH-BASED CRSN FRAMEWORK

Algorithm	50 nodes	100 nodes	150 nodes
Hop count analysis			
PSO	7	13	15
ROA	5	9	13
CSO	13	11	13
EHO	7	14	11
HCSEHO	9	8	9
Energy Harvesting analysis(mJ)			
PSO	0.000397	0.000205	0.00081
ROA	0.00039	0.000288	0.000167
CSO	0.000883	0.000916	0.000894
EHO	0.000262	0.000168	0.000444
HCSEHO	0.000255	0.000426	0.000806
Throughput analysis (Mbps)			
PSO	0.87971	0.94292	0.33254
ROA	0.63734	1.0423	0.48755
CSO	0.79939	0.41044	0.59607
EHO	0.89511	0.40302	0.82279
HCSEHO	0.97063	1.0942	1.09
Outage probability analysis ($x10^{-4}$)			
PSO	1038	656	1143
ROA	905	814	958
CSO	1157	865	973
EHO	1258	985	1011
HCSEHO	811	761	736

TABLE 4.2 DATASET 2 ESTIMATION OF EH-BASED CRSN FRAMEWORK

Algorithm	50 nodes	100 nodes	150 nodes
Hop count analysis			
PSO	4	13	15
ROA	8	14	8
CSO	6	10	10
EHO	5	6	8
HCSEHO	5	5	7
Energy Harvesting analysis(mJ)			
PSO	0.000442	0.000573	0.000833
ROA	0.000488	0.000254	0.000832
CSO	0.000748	0.00027	0.000683
EHO	0.000937	0.00057	0.0006
HCSEHO	0.000382	0.000958	0.000302
Throughput analysis (Mbps)			
PSO	0.52779	0.83525	0.79
ROA	0.33098	0.98931	0.69596
CSO	0.3828	0.92484	0.75083
EHO	0.56369	1.0264	0.77329
HCSEHO	0.64224	1.0534	0.91765

Outage probability analysis (x10^{-4})			
PSO	719	905	1247
ROA	784	620	1111
CSO	886	783	1098
EHO	682	823	956
HCSEHO	729	1286	677

TABLE 4.3 DATASET 3 ESTIMATION OF EH-BASED CRSN FRAMEWORK

Algorithm	50 nodes	100 nodes	150 nodes
Hop count analysis			
PSO	9	6	15
ROA	9	9	11
CSO	7	3	14
EHO	4	9	12
HCSEHO	4	7	4
Energy Harvesting analysis(mJ)			
PSO	0.000767	0.000386	0.000334
ROA	0.000153	0.000607	0.000875
CSO	0.000812	0.000467	0.000548
EHO	0.000332	0.000938	0.000604
HCSEHO	0.000876	0.000553	0.000431
Throughput analysis (Mbps)			
PSO	0.54191	0.63534	0.47915
ROA	0.7174	0.37203	0.50266
CSO	0.64761	0.89597	0.64822
EHO	0.68362	0.43176	0.56989
HCSEHO	1.004	1.0836	0.89261
Outage probability analysis (x10^{-4})			
PSO	1005	921	983
ROA	1058	1146	1233
CSO	1292	1220	1158
EHO	783	1076	1105
HCSEHO	762	1037	877

4.6 Conclusions

This study has devised an effective energy harvesting-based Cognitive Radio Sensor Network (CRSN) framework for the transmission of medical data. The framework incorporates the HCSEHO optimization strategy to enhance transmission performance. Optimal cluster head selection was optimized through a multi-objective function considering factors such as "distance, energy harvesting, throughput, hop count, outage probability, and delay." These constraints were taken into account to improve data transmission rates without introducing delays. In the analysis of dataset 1, with 100 nodes, the proposed HCSEHO outperforms PSO, ROA, CSO, and EHO by 0.48%, 79.29%, 10.90%, and 44.92%, respectively, in terms of energy harvesting. The findings confirm the superiority of the developed framework utilizing HCSEHO in medical data transmission compared to existing techniques.

CHAPTER 5

5. TRUST-AWARE CR NETWORK WITH ENERGY HARVESTING

5.1 Introduction

Energy Harvesting can extract the energy of the surrounding conditions, which is considered to be an efficient technique for assuring the energy level, which is also able to combine with the CR systems for prolonged the lifetime of CR-SN and also able to minimize their deployment cost [124]. Two broadly used energy harvesting architectures are observed to be Time Switching (TS) and Power Splitting (PS) [125]. When considering PS model, the signal power received is separated into 2-segments, in that some fraction is utilized to gather energy, and the remaining is employed to process the received signal [126]. On the other hand, in TS architecture, the transmission slot is separated into two processes, where the former process performs the energy harvesting using the surrounding conditions, and further, the generated energy is utilized to perform the data transmission at the latter process [127]. The SUs in CR networks seem to be susceptible when analyzing both internal and external attacks. Moreover, the Secret messages passed over the CR Network led to overhead via the malicious EDs because of the broadcast characteristics of radio propagation [128]. Therefore, in addition to maintaining a constant transmission, the goal is to protect the CRN transfer while taking malevolent eavesdropping into account. Owing to the current technological advancements and rising processing power, it is equally important to have highly secure communication to prevent harmful assaults. [129].

Energy harvesting elevates the system to be self-independent in wireless devices. Following this, the challenging operation of reaching the environments in the case of sensors fixed within the human body [130] is possible. Further, this mechanism extends the computation time required for wireless devices before the requirement of battery recharge. The energy harvesting task transmits received energy like “solar, wind, electromagnetic, etc.” into electric energy [131]. Radio Frequency (RF) sources are very helpful for harvesting energy for wireless devices, in which energy harvesting with RF has covered a broad range and also has powered a huge count of devices [132]. For RF-energy harvesting, harvested energy is taken through ambient or dedicated sources. Dedicated sources are considered to be consistent [133]. On the other hand, they are limited by their cost inefficiency along with power safety [134].

While the network seems to be under open access and is vulnerable to external threats, CRN security is at its peak [135]. Eavesdropper makes the network intrusion [136] and also, leads to energy depletion in the energy gathering nodes to change them to erroneous nodes to reduce safety. Conventional CRNs makes high efforts to improve the security and also reliability tradeoff of CRN, which depends on energy harvesting. In order to support the CRN, the cooperative jamming method and artificial noise were devised in [137] with the purpose of improving network security. Additionally, in [138], algorithms for energy harvesting are created using an ideal relay selection to provide an improved trade-off between the security and efficiency of the primary transmission and the secondary transmission. The study conducted an analysis of an underlay CRN consisting of a set of primary nodes and two secondary nodes. The analysis focused on the secrecy outage performance. However, the CRN faced challenges in terms of network performance. To address this, an efficient heuristic algorithm was developed to improve the performance of the CRN in data transmission, taking into account energy harvesting and trust assurance [139].

The following are the main contributions of the developed EH-CRN model, which includes trust computation and energy harvesting.

- To develop an extremely effective routing protocol in CRN for performing better MDT considering the energy harvesting and trust computation for enhancing the lifetime of the network and also improving the security of the data transmission.
- To develop a more advanced heuristic technique called SA-LBOA that focuses on improving trust performance and energy harvesting in EH-CRN. This technique aims to optimize the selection of cluster heads between source and destination nodes, taking into account multiple constraints such as trust computation, energy harvesting, hop count, throughput, and outage probability. The ultimate goal is to support medical applications.
- To evaluate the effectiveness of the trust-aware CRN-based MDT model in comparison to standard heuristic techniques based on the analysis of multiple objectives.

5.2 Proposed System Model

In the context of the Internet of Things (IoT), several heterogeneous wireless devices are interconnected to provide a wide range of applications such as personal healthcare, smart cities, transportation and smart homes. The integration of diverse devices in the IoT network leads to an increased demand on the frequency spectrum. Hence, CR technology is widely regarded as the definitive option for optimizing spectrum use in the field of data transmission. The growing number of devices in the Internet of Things (IoT) places more strain on the limited frequency resources available in the Industrial Scientific Medical (ISM) bands, which are managed by Cognitive Radio (CR) technology to address issues of congestion. An efficient routing protocol has to be created for cognitive radio-based Internet of Things (CR-based IoT). However, this job is tough due to the diverse and dynamic nature of the IoT nodes and spectrum. While there is a significant amount of research being conducted on the development of routing algorithms, these efforts have not been successful in effectively managing the routing table. Furthermore, the majority of the studies do not prioritize the integration of cognitive radio (CR) with an optimization algorithm to improve the efficiency of data transmission in the context of trust inside the Internet of Things (IoT). In light of the CR situations [140] [141], the malfunctioning node engages in assaults against the regular node and amplifies the reputation of certain other malevolent users. Furthermore, this also results in a decrease in the confidence level of the well-behaving nodes, which subsequently leads to a fall in both network and energy efficiency [142]. Therefore, the objective is to create a highly effective routing protocol that functions as an optimization algorithm to improve the performance and energy harvesting of Cognitive Radio Networks (CRN), with a specific emphasis on medical data transmission. The architectural diagram of the trust-aware MDT model built for CRN is presented in Figure 5.1.

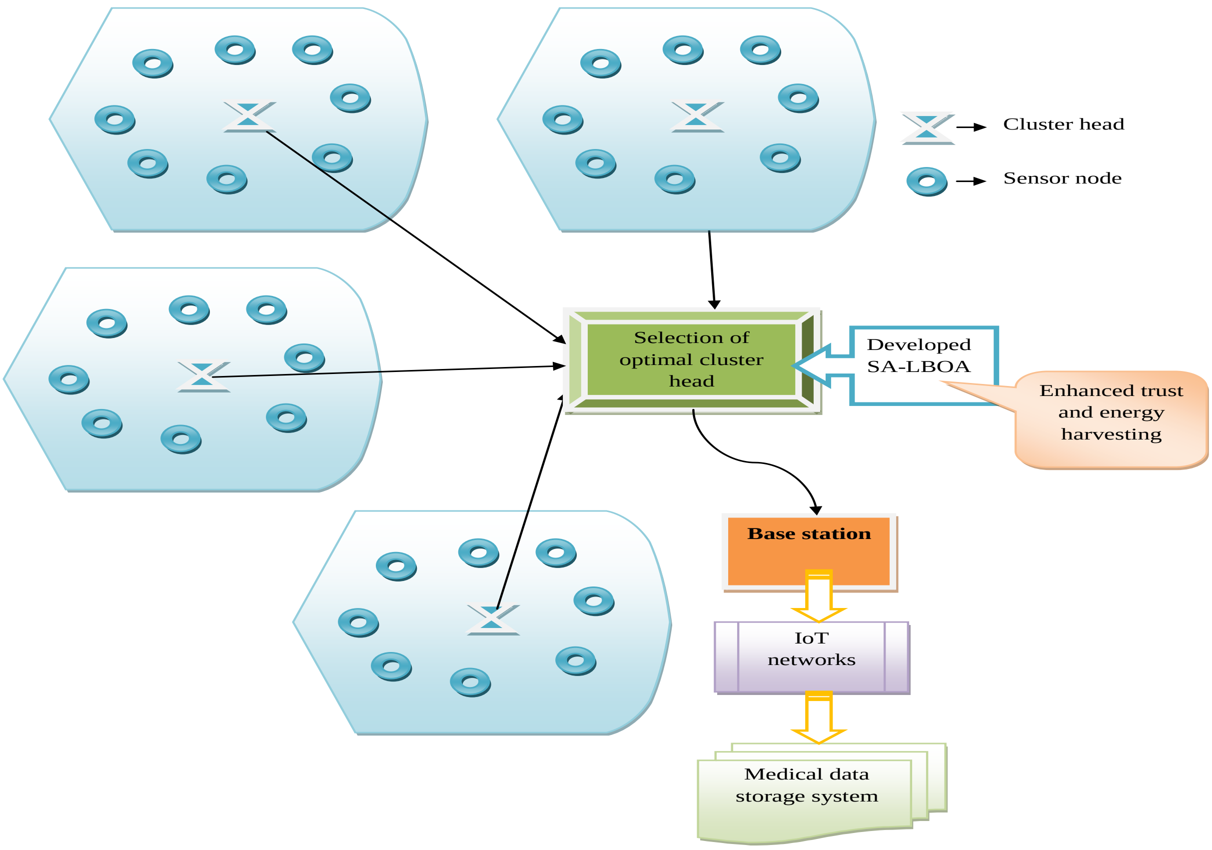


Fig. 5.1 Trust-Aware Model in EH-CRN

A novel optimization approach called SA-LBOA has been developed to improve trust performance and energy harvesting in the CR Network. To address the problems that arise while transferring medical data over CRN, we resolve them by implementing an optimum cluster head selection method. This method improves energy harvesting during data transmission by routing it across all the nodes in the network. This aids in achieving the multi-objective function while taking into account restrictions such as "trust, hob count, throughput, energy harvesting, and outage probability" in order to enhance the overall system performance. Moreover, this optimization of performance results in enhanced longevity of the network and increased energy acquisition, along with reliable data transfers.

5.2.1 Description of proposed SA-LBO Algorithm

The implemented Cognitive Radio Network (CRN) executes Health Data Transmission (MDT) with the optimal CH selection through the proposed SA-LBOA, aiming to achieve improved energy harvesting and trusted performance for enhanced MDT effectiveness. LBOA [143] algorithm is considered here because of its advantages against not falling in to local minimum easily. However, LBOA requires certain changes to address multiple optimization problems within benchmark functions. To enhance LBOA's efficiency, adaptive concepts are incorporated, resulting in the development of Adaptive LBOA, termed SA-LBOA. Here the random self-adaptive parameter Rdn is indicated in Eq. (5.1).

$$Rdn = \frac{(BstFt - CrnFt)}{(WrtFt - CrnFt)} \tag{5.1}$$

$BstFt$ - best fitness value,

$CrnFt$ - current fitness

$WrtFt$ - worst fitness values

Rdn will be in the range (0, 1)

Rdn is used to update position of the ladybugs and population size.

$L(0)$-Initial population size of ladybugs

$L(m_{maX})$- final population of ladybugs.

Generally $L(0) \geq L(m_{maX})$

According to the population size, the optimal objective function will be finalized.

Suppose the modification of a population member occurs depending on the positions of another members within the populations. k^{th} ladybug's position among the population is denoted by $y(m)$ at m^{th} iteration. The updated position of k^{th} ladybug is computed in Eq. (5.2).

$$y_k(m+1) = y_k(m) + Rdn \times (y_n(m) - y_k(m))$$
$$+ Rdn \times (y_n(m) - y_{n-1}(m)) + Rdn \times |D_k|^{-\frac{m}{P(m)}} \times y_k(m) \tag{5.2}$$

D_k - indicates the ratio of the k^{th} ladybug value to the entire ladybugs in the m^{th} iteration and is calculated by using Eq.(5.3).

$$D_k = \frac{f(y_k(m))}{\sum_{s=1}^{Pm} f(y_s(m))} \tag{5.3}$$

The location of the n^{th} ladybug is calculated by using the random roulette wheel selection method, which will help to update the k^{th} ladybug's location.

Then, mutation process is taken to establish the un-covered sample space to avoid the local minima problem.

k^{th} ladybug gets into the mutations by its decision variables q_r as given Eq. (5.4).

$$q_r = round(q * \mu_r) \tag{5.4}$$

μ_r : Rate of mutation; q: variable size.

Due to the random movements of ladybugs, there will be loss in the total ladybugs in a given direction. This reduction in the count of the lady-bugs takes place at the time of searching in LBOA population and is indicated as in Eq. (5.5).

$$L(m+1) = round\left(L(m) - Rdn \times L(m)\left(\frac{NFE}{NFE_{maX}}\right)\right) \tag{5.5}$$

NFE - evaluation of the function count

NFE_{maX} - maximum value of NFE

This condition will continue till function evaluations satisfy termination condition.

If it does not satisfy the termination condition, the updated new position of the ladybug is obtained through Eq. (6).

$$L(m+1) = round\left(L(m) - Rdn \times L(m)\left(\frac{m}{m_{maX}}\right)\right) \tag{5.6}$$

The variable m denotes the present iteration and m_{maX} denotes maximum iteration. The pseudocode for SA-LBOA is shown in Algorithm 5.1.

Algorithm 5.1: Developed SA-LBOA [147]

Generate the ladybug population
determine the lower-cost function of the ladybug
For all ladybugs do
  determine the objective function of ladybugs
  compute the random parameter adaptively, as shown in Eq. (5.1)
  If $(Rdn > r_Q)$
    $n = 0;$
    While $(n < 2)$ do
      Determine n^{th} ladybug based on the roulette wheel selection method
    End while
    Determine the coefficient D_k as shown in Eq. (5.3)
  Else
    Compute the decision variables q_r in the feasible region as given in Eq. (5.4).
  End if
  If $(y_k(m+1) < y_{miN})$ do
    $(y_k(m+1) = y_{miN})$
  End if
  If $(y_k(m+1) > y_{maX})$ do
    $(y_k(m+1) = y_{maX})$
  End if
End for
Arrange the population based on the cost function values
Get the best solution as the final population outcome at the current iteration
End

5.2.2 Description of the Energy Harvesting Model

The Energy Harvesting (EH) model [148] entails a fixed Single User (SU) source equipped with multiple antennas (M_t) associated with a Primary User (PU) pair. The Hybrid Base Station (HBS) is responsible for energy transmission via antenna 'f' and acquiring data from the SU, which is situated under the antennas. Additionally, the SU adopts a spectrum-sharing paradigm for energy harvesting, ensuring that the total power for both energy and data transmissions remains below the achievable interference limit R_u of the PU. The SU source operates with a limited battery storage capacity, necessitating the harvesting of sufficient energy from both the

PU and Hybrid BS networks to facilitate the data transmission. The energy $\hat{R}_{ES}$, established at the SU's starting point in the preceding time slot before data transmission, is computed using Eq. (5.7).

$$\hat{R}_{ES} = \upsilon(Q_{PT}\|f_{TS}\|^2 + Q_E\|i_{ES}\|^2) \tag{5.7}$$

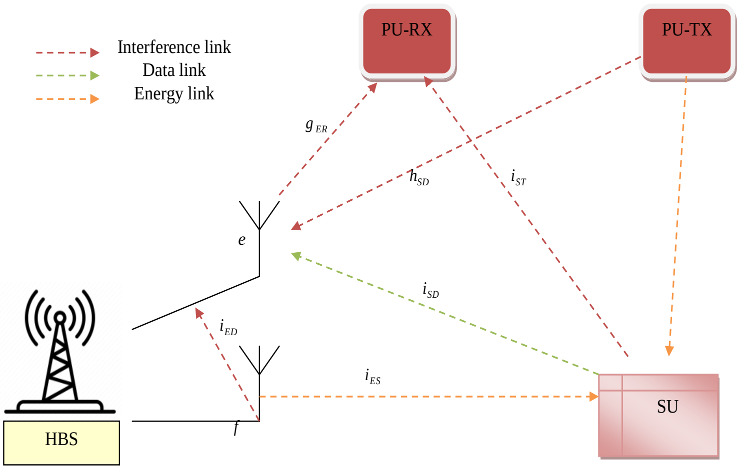


Fig. 5.2 EH-CRSN with single SU

5.2.3 Description of the Trust Model

As node 'b' consistently sends a higher volume of messages received from node 'a,' the possibility of deeming node 'b' a trusted neighbor of node 'a' arises. This likelihood is leveraged for trust computation. Let '$Pc_{a,b}(Tm1)$' represent the count of packets successfully transmitted between nodes 'a' and 'b' at time Tm. The ratio '$PcR_{a,b}(Tm1)$,' computed as the ratio of $PcR_{a,b}(Tm1)$ to the total packets forwarded by all one-hop neighbors $\left(\sum_{c=1}^{c_a(Tm)} Pc_{a,c}(Tm1)\right)$ is given as in Eq.5.8

$$PcR_{a,b}(Tm) = \frac{Pc_{a,b}(Tm)}{\left(\sum_{c=1}^{c_a(Tm)} Pc_{a,c}(Tm)\right)} \tag{5.8}$$

Further, to determine the trust values of the nodes, direct and indirect trust values are calculated based on the Eq. (5.9) and Eq. (5.10) respectively.

$$Trst_{a,b}^{dirct}(Tm1) = \alpha \times Pc_{a,b}(Tm1) \tag{5.9}$$

α - weighing factor lies in the interval $[0,1]$.

$$Trst_{a,b}^{indirct}(Tm1) = \frac{\sum_{d\in A, d\neq b}\left(Trst_{a,d}^{dirct}(Tm1)\times Trst_{d,b}^{indirct}(Tm1)\right)}{\sum_{d\in A, d\neq b} Trst_{a,d}^{dirct}(Tm1)} \tag{5.10}$$

Total Trust value is given by Eq. (5.11)

$$Trst_{a,b}(Tm1) = \frac{\phi_1 Trst_{a,b}^{dirct}(Tm1) + \phi_2 Trst_{a,b}^{indirct}(Tm1)}{p_a(Tm)} \quad (5.11)$$

The weighing factors were indicated by φ_1 and φ_2 that ranges in between $\varphi_1, \varphi_2 \in [0,1]$. The sending nodes are classified as malicious node when $0 < Trst_{a,b} < \varphi_1$, an uncertain node when the node with the trust value of φ_1, and the trusted node when of $\varphi_1 < Trst_{a,b} \leq 1$.

5.3 Derivation of Multi-Objective Function

The developed MDT model in CRN with trust computation and energy harvesting makes the optimal selection of cluster head using the developed SA-LBOA to achieve the multi-objective function including "trust, energy harvesting, hob count, throughput, and outage probability". The objective function O_fn for the developed SA-LBOA-based optimal cluster head selection is mentioned in Eq. (5.12).

$$O\_fn = \underset{\{Cl\_hd_x^{opt}\}}{argmin} \left(\frac{1}{Fg_5}\right) \quad (5.12)$$

The optimally selected cluster heads are denoted by $Cl\_hd_x^{opt}$ for performing efficient MDT in CRN. The objective Fg_5 is derived from the below-mentioned equations.

$$Fg_1 = \alpha + \left((1-\alpha) * \left(\frac{1}{Trst}\right)\right) \quad (5.13)$$

$$Fg_2 = \beta * Fg_1 + \left((1-\beta) * R_e\right) \quad (5.14)$$

$$Fg_3 = \chi * Fg_2 + \left((1-\chi) * (Hcn)\right) \quad (5.15)$$

$$Fg_4 = \delta * Fg_3 + (1-\delta) * \left(\frac{1}{Thrgh}\right) \quad (5.16)$$

$$Fg_5 = \varepsilon * Fg_4 + (1-\varepsilon) * \left(\frac{1}{OutP}\right) \quad (5.17)$$

The terms alpha α, gamma χ, and omega δ are taken as the value of 0.2. Moreover, the beta β value is considered as 0.3, and also, the epsilon ε contains 0.1.

The objectives constraints are performed in the designed MDT model in CRN are given as "trust, energy harvesting, hob count, throughput, and outage probability" are given below.

The harvested energy R_e is "the average energy which is presented in the alive node," as in Eq. (18).

$$R_e = R_{nk} - \left(R_{nk}^{ck} + R_{nk}^{sk}\right) \quad (5.18)$$

Here, the energy is denoted by R_{nk} at all nodes nk, the necessary energy for data gathering is indicated by R_{nk}^{ck}, and the necessary energy for transmitting data is mentioned by R_{nk}^{sk}.

Throughput $Thrgh$ is “the successful data is delivered over a communication channel in the network,” as in Eq. (5.19).

$$Thrgh = \frac{\sum(Pc_{sk} * aPc_{sk})}{tmK} \tag{5.19}$$

The average packet size is shown by aPc_{sk}, and successive packet count is indicated by Pc_{sk}. Outage probability $OutP$ is “the probability of the information rate is less than the required threshold information rate which is occurred within a certain period” which is denoted in Eq. (5.20).

$$OutP = \frac{Out_{ct}}{U_n} \tag{5.20}$$

Here, the term Out_{ct} denotes the outage counter and U_n indicates the number of times taken to determine the probability of an outage. This outage probability is ranged between $\left[0, 5\times10^{-4}\right]$. Hop count Hcn is used “to determine the best possible route to a host or network”.

5.3.1 Optimization of Cluster Heads in CRN

The SA-LBOA algorithm is utilized to choose and optimize the cluster heads by taking into account the balance between intra-cluster communication, distance from the cluster head to the base station, and the remaining energy of nodes for cluster head selection. The system consists of a group of sensor nodes that are connected to form clusters. The cluster head is selected using the SA-LBOA algorithm, which takes into account all cluster heads. The cluster formation involves assigning time slots based on the cluster head's role in receiving messages or data from other nodes. The cluster head plays a crucial role in facilitating data gathering from all the nodes within the cluster. Upon receiving all the necessary information from the nodes, the cluster head initiates the transfer of medical data to the base station, followed by the process of data aggregation. Subsequently, the process of re-clustering and data transmission occurs at each iteration in order to reach the terminating nodes. If the size of the cluster is smaller than the specified threshold, it will be merged with nearby clusters to optimize data transmission. The optimum solutions obtained using the developed SA-LBOA algorithm are shown in Fig. 5.2

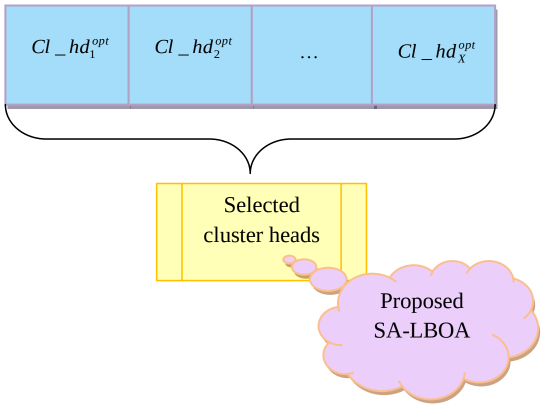


Fig. 5.3 Optimized Solutions through Proposed SA-LBOA

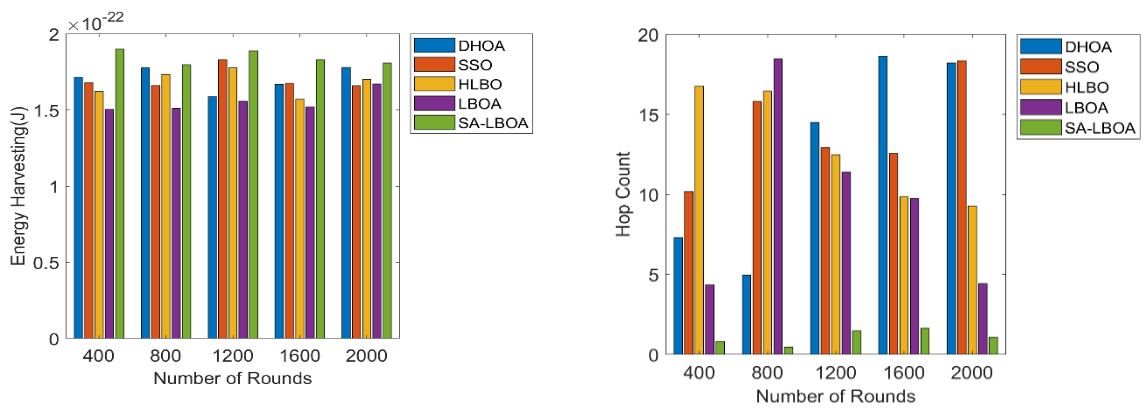
5.4 Results and Discussions

5.4.1 Experimental setup

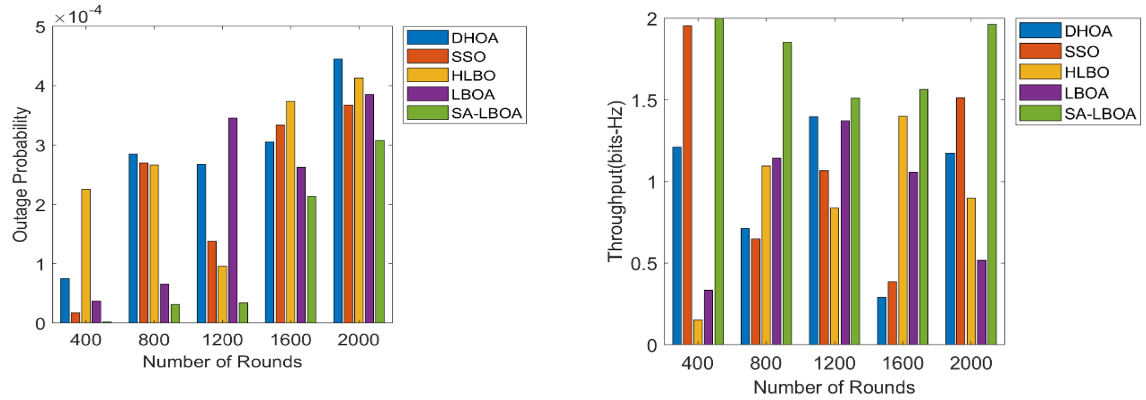
The developed trust computation and energy harvesting-based MDT model in CRN using the implemented SA-LBOA has utilized MATLAB 2020a as the implementation platform and also for performing various analyses on the developed model. Also, the developed SA-LBOA was compared with conventional techniques like “Deer Hunting Optimization Algorithm (DHOA) [144], Shark Smell Optimization (SSO) [145], Hybrid Leader-Based Optimization (HLBO) [146] and LBOA [143]” to determine the trust performance and energy harvesting of the implemented model. The normalized energy is referred as the computation of the energy consumption of the fully loaded system to the total energy consumption of the system.

5.4.2 Evaluation of Developed algorithm – Dataset-1

The analysis of the developed MDT model in CRN with trust computation and energy harvesting is done based on dataset 1, as shown in Fig.5.4



(a) (b)

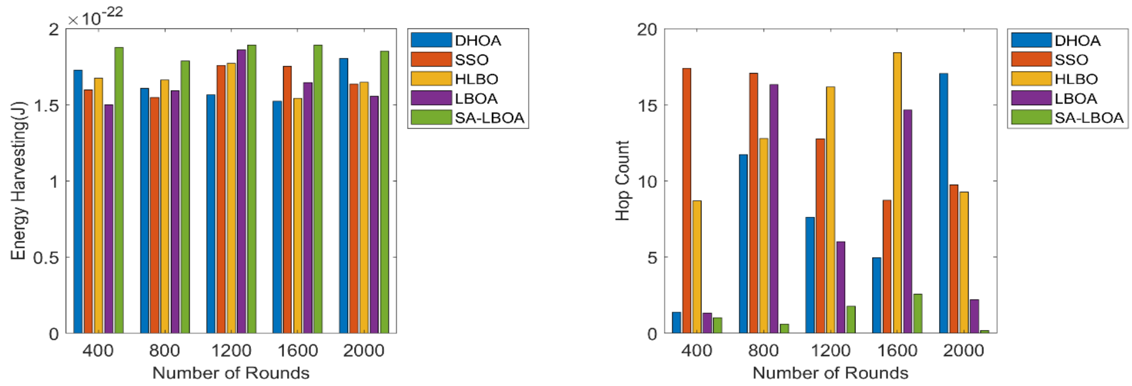


(c) (d)

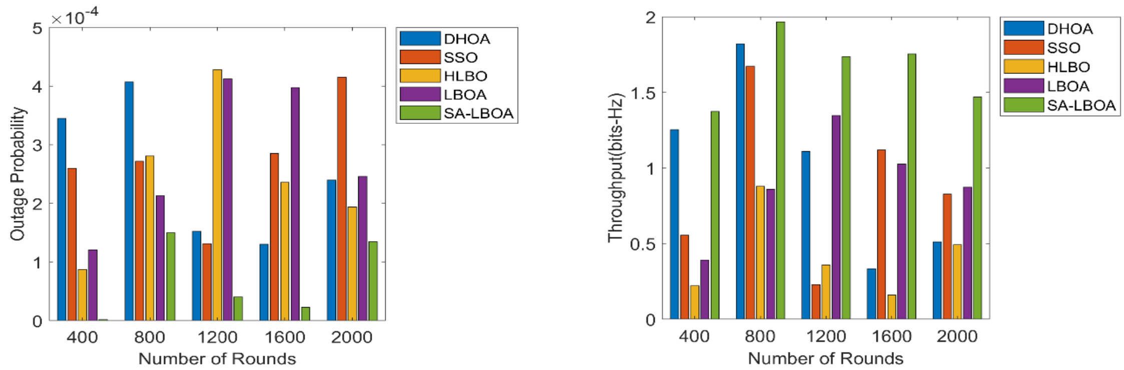
Fig. 5.4. Validating of Trust-Aware EH-CRSN Model (Dataset-1) in terms of "(a) Energy Harvesting, (b) hop count, (c) outage probability, (d) throughput

5.6.3 Evaluation of Developed algorithm – Dataset-2

Evaluating the developed MDT model in CRN with trust computation and energy harvesting is performed for testing its efficiency according to dataset 1, as shown in Fig.5.5.



(a) (b)



(c) (d)

Fig. 5.5 Validating of Trust-Aware EH-CRSN Model (Dataset-2) in terms of "(a) Energy Harvesting, (b) hop count, (c) outage probability, (d) throughput

5.4.4 Evaluation of Developed algorithm – Dataset-3

The implemented MDT model in CRN with trust computation and energy harvesting is considered for the comparative analysis with conventional heuristic algorithms based on dataset 3, as shown in Fig.5.5.

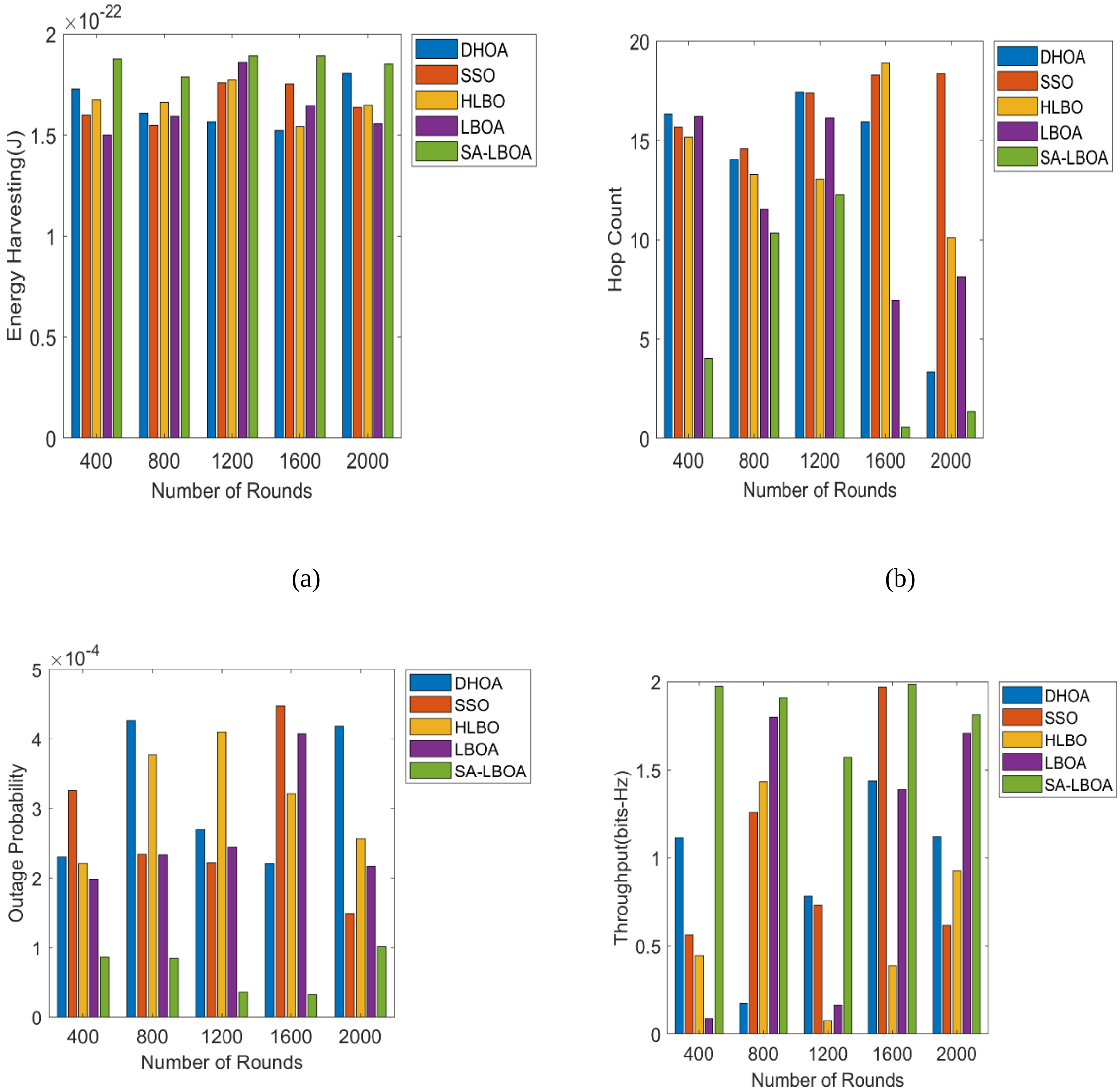


Fig. 5.6 Validating of Trust-Aware EH-CRSN Model (Dataset-1) in terms of "(a) Energy Harvesting, (b) hop count, (c) outage probability, (d) throughput

5.4.5 Statistical analysis on Different Node Ranges

The statistical analysis is carried out by varying the node ranges as 50, 100, and 150, as shown in Table 2, Table 3, and Table 4. The developed SA-LBOA attains 0.078%, 0.02%, 0.04%, and 0.05% better trust values than DHOA, SSO, HLBO, and LBOA based on dataset 1. Similarly, higher performance enhancements are observed in two further dataset-based analyses of the proposed model.

TABLE 5.1 COMPARATIVE STATISTICAL ANALYSIS WITH 50 NODES

Description	DHOA	SSO	HLBO	LBOA	SA-LBOA
Dead node analysis					
Best	0	0	0	0	0
Mean	0.022511	0.022511	0.022511	0.022511	0.022011
Worst	1	2	2	3	2
Standard deviation	0.14838	0.16438	0.15498	0.17036	0.15343
Median	0	0	0	0	0
Normalized energy analysis					
Worst	0.000466	0.000478	0.000478	0.000478	0.000478
Best	0	0	0	0	0
Median	0.000399	0.000401	0.000402	0.000402	0.000372
Mean	0.000253	0.000252	0.000255	0.000251	0.000248
Standard deviation	0.000199	0.000205	0.0002	0.000206	0.000206
Trust analysis					
Worst	6.44×10^{-05}	0.000144	0.000495	0.000275	0.000239
Best	0.99922	0.99984	0.99958	0.99948	0.99999
Median	0.49017	0.50185	0.51125	0.50187	0.48433
Mean	0.49279	0.49754	0.50328	0.50388	0.49508
Standard deviation	0.2893	0.29043	0.28744	0.28643	0.2871
Energy harvesting analysis					
Worst	0.000197	0.000308	5.49×10^{-05}	0.00011	9.57×10^{-05}
Best	0.99991	0.99996	0.99892	0.99992	0.99905
Median	0.51612	0.51574	0.51583	0.50048	0.48461
Mean	0.51061	0.51079	0.50896	0.49866	0.4928
Standard deviation	0.29078	0.28626	0.28555	0.29279	0.29315
Hop count analysis					
Best	0.000894	6.60×10^{-05}	0.00011	0.000158	0.00028
Mean	0.49428	0.5003	0.48685	0.49976	0.50165
Worst	0.99997	0.99932	0.99979	0.99976	0.99988
Standard deviation	0.28729	0.29164	0.28685	0.29218	0.28763
Median	0.49894	0.49949	0.48159	0.50081	0.51017
Throughput analysis					
Mean	0.49716	0.51233	0.50506	0.50569	0.49517
Best	0.99947	0.99993	0.99984	0.99998	0.99994
Median	0.49146	0.51363	0.50426	0.50155	0.49906
Worst	8.67×10^{-05}	0.000403	0.000664	0.001245	5.96×10^{-06}
Standard deviation	0.29405	0.28625	0.29115	0.29114	0.28851
Outage probability analysis					
Worst	0.9999	0.9992	0.99996	0.99985	0.99855
Best	0.000163	0.000439	0.001753	0.000412	0.000188
Median	0.51211	0.49303	0.50011	0.51244	0.52412
Mean	0.50665	0.50097	0.50238	0.50332	0.51415
Standard deviation	0.28823	0.29259	0.28642	0.28632	0.28927

TABLE 5.2 COMPARATIVE STATISTICAL ANALYSIS WITH 100 NODES

Description	DHOA	SSO	HLBO	LBOA	SA-LBOA
Dead node analysis					
Best	0	0	0	0	0
Standard deviation	0.23322	0.24297	0.23244	0.23671	0.24203
Mean	0.046523	0.045023	0.045023	0.045023	0.044522
Worst	2	4	3	3	3
Median	0	0	0	0	0
Normalized energy analysis					
Median	0.000402	0.000414	0.000417	0.000416	0.000416
Worst	0.000483	0.000481	0.000485	0.000478	0.000483
Best	0	0	0	0	0
Standard deviation	0.000199	0.000195	0.000195	0.000197	0.000197
Mean	0.000267	0.000264	0.000263	0.000263	0.000262
Trust analysis					
Worst	0.00014	0.000264	0.001133	0.000161	0.001533
Best	0.99963	0.99973	0.99985	0.99981	0.99934
Mean	0.49166	0.50128	0.49086	0.50327	0.51104
Standard deviation	0.29024	0.2869	0.28927	0.29061	0.28259
Median	0.49141	0.50657	0.5022	0.51217	0.50509
Energy harvesting analysis					
Best	0.99999	0.99786	0.99986	0.99987	0.99962
Worst	0.000535	0.000351	0.001245	0.000189	0.000442
Median	0.48985	0.49863	0.50204	0.49251	0.49508
Standard deviation	0.28646	0.28803	0.28224	0.29227	0.28874
Mean	0.49454	0.4994	0.502	0.49819	0.4954
Hop count analysis					
Best	0.001521	0.001262	0.000494	0.000115	0.000297
Worst	0.99924	0.99986	0.99923	0.99965	0.9998
Mean	0.49295	0.49898	0.49995	0.49801	0.50693
Median	0.48613	0.49383	0.5051	0.50519	0.50603
Standard deviation	0.28161	0.28453	0.28523	0.28499	0.29215
Throughput analysis					
Mean	0.50652	0.50041	0.50924	0.50118	0.4825
Worst	0.000498	3.11×10^{-05}	3.56×10^{-05}	0.000161	0.001437
Median	0.51884	0.4952	0.50785	0.50003	0.46849
Best	0.99993	0.99972	0.99845	0.99911	0.99967
Standard deviation	0.28875	0.28985	0.28747	0.28729	0.28707
Outage probability analysis					
Best	0.000745	0.000578	0.001414	7.38×10^{-05}	0.000857
Median	0.49914	0.52135	0.53182	0.49737	0.50379
Mean	0.49885	0.51466	0.52012	0.50021	0.50187
Standard deviation	0.28914	0.28604	0.28593	0.28716	0.28631
Worst	0.99938	0.99989	0.99985	0.99979	0.99985

TABLE 5.3 COMPARATIVE STATISTICAL ANALYSIS WITH 150 NODES

Description	DHOA	SSO	HLBO	LBOA	SA-LBOA
Dead node analysis					
Best	0	0	0	0	0
Mean	0.070035	0.068034	0.067534	0.068534	0.067034
Worst	3	5	3	3	3
Standard deviation	0.29186	0.3106	0.2864	0.28964	0.29933
Median	0	0	0	0	0
Normalized energy analysis					
Best	0	0	0	0	0
Mean	0.000272	0.000264	0.000265	0.000266	0.000263
Worst	0.000483	0.000466	0.000474	0.000474	0.000469
Standard deviation	0.000194	0.000192	0.000191	0.000191	0.00019
Median	0.000407	0.000411	0.000416	0.000411	0.00041
Trust analysis					
Best	0.99971	0.99955	0.99947	0.99922	0.99976
Worst	0.001101	0.00013	0.000511	0.001125	0.000319
Mean	0.50456	0.50826	0.51022	0.50816	0.4881
Median	0.50403	0.50872	0.5227	0.51088	0.48391
Standard deviation	0.2862	0.28406	0.28732	0.29075	0.29206
Energy harvesting analysis					
Median	0.49271	0.48009	0.49089	0.49679	0.51475
Mean	0.50081	0.48973	0.50099	0.49591	0.51306
Best	0.9999	0.99973	0.99954	0.99987	0.99917
Worst	0.000435	0.000365	0.00014	0.000189	0.000429
Standard deviation	0.29157	0.28905	0.2841	0.29481	0.28713
Hop count analysis					
Best	0.000442	0.001267	0.000362	0.000115	4.77×10^{-05}
Mean	0.49443	0.50863	0.50024	0.49446	0.4959
Worst	0.99906	0.99956	0.99863	0.99966	0.99983
Standard deviation	0.28524	0.28932	0.28789	0.2867	0.29059
Median	0.47964	0.50651	0.49933	0.4908	0.49863
Throughput analysis					
Mean	0.50611	0.49167	0.49148	0.49478	0.50079
Best	0.99937	0.9991	1	0.99859	0.99983
Standard deviation	0.28958	0.28562	0.28571	0.28458	0.29085
Worst	9.34×10^{-05}	0.000258	0.000268	0.000161	0.000343
Median	0.52003	0.48284	0.48758	0.49227	0.5011
Outage probability analysis					
Best	9.95×10^{-05}	2.26×10^{-06}	0.00059	0.000582	0.000216
Worst	0.99864	0.99895	0.99895	0.99979	0.99973
Standard deviation	0.29406	0.28739	0.28686	0.28458	0.28536
Mean	0.50413	0.50815	0.49884	0.49944	0.50228
Median	0.49917	0.51745	0.50344	0.49804	0.51405

5.5 Conclusion

A very effective optimization method was deployed in the EH CRN network to improve trust performance and energy collection. The problems encountered during the transmission of medical data over CRN were resolved by implementing optimal cluster head selection for routing across all nodes to improve energy harvesting during data transmission. This approach has achieved a multi-objective function that takes into account constraints such as trust, energy harvesting, hop count, throughput, and outage probability to enhance the overall performance of the system. The suggested model outperformed the standard methods, as evidenced by the above study findings. Subsequent research will assess the efficacy of contemporary deep learning models in order to yield more precise and dependable results. Furthermore, future study will thoroughly examine the resource allocation process in the multi-hop CRN. Hence, the assessment and consideration of forecasting the interference and link quality in the CRN will be undertaken as part of future research.

CHAPTER 6

THESIS CONCLUSION

In conclusion, this thesis endeavors to contribute significantly to the advancement of healthcare communication systems by focusing on the symbiotic integration of cognitive radio and energy harvesting within the context of IoMT. The overarching objective is to establish a robust framework for the secure transmission of medical data, ensuring the confidentiality and integrity of sensitive information. By merging cognitive radio technology with energy harvesting capabilities, the proposed system not only enhances the efficiency and reliability of data transmission but also addresses the crucial aspect of sustainability. The integration of energy harvesting mechanisms aims to extend the operational lifetime of the Cognitive Radio (CR) Network, ensuring continuous and resilient connectivity for medical devices. Through these innovations, this research strives to pave the way for more resilient and sustainable healthcare networks, fostering advancements in patient care, data security, and overall system longevity.

This study initially implemented the CR routing protocol within the IoT to facilitate the efficient transmission of clinical data, employing the novel SR-CHGWO. This algorithm considered multi-objective constraints for CH selection, encompassing parameters such as energy, throughput, distance, time delay, data rate, and outage probability. The assessment of the SR-CHGWO revealed a substantial improvement of 42.5%, 27.2%, 33.2%, and 20.29% in node power against PSO, JAYA, GWO and CHIO respectively. These findings unequivocally demonstrate the efficacy of the proposed routing protocol in enhancing medical data transmission within the cognitive routing framework of IoT. Furthermore, simulation results underscore the superior computational efficiency of the SR-CHGWO algorithm when contrasted with traditional optimization methods. Furthermore, this study has devised an effective EHCRSN framework for the transmission of health data, leveraging the optimization prowess of HCSEHO to amplify the overall performance. The optimization process focused on selecting the optimal cluster heads by addressing a multi-objective function that encompasses parameters such as "distance, energy harvesting, throughput , hop count, outage probability, and delay". All these constraints were strategically considered to enhance the data transfer rates without compromising on delay. In comparison to PSO, ROA, CSO and EHO the proposed

HCSEHO exhibited a notable performance improvement of 0.49%, 79.28%, 10.91%, and 44.91%, respectively, particularly in terms of energy harvesting when considering a dataset of 100 nodes in Dataset-1. Furthermore, it was ascertained that the developed framework, empowered by HCSEHO, outperforms existing medical data transmission techniques, highlighting its superiority in the realm of efficient and optimized medical data transmission.

Finally, a highly effective optimization mechanism was employed to optimize data transmission within the Cognitive Radio Network (CRN), significantly improving trust performance and the viability of nodes after 2000 iterations. To address challenges arising during data transmission over the CRN, an optimal cluster head selection process was executed, covering all nodes to enhance throughput and mitigate outage probability. This approach achieved a multi-objective function, incorporating constraints such as hop count, throughput, and outage probability ultimately enhancing overall system performance even in the presence of mis behaving nodes. The performance boost facilitated by the developed SA-LBOA not only extended the network lifespan but also instilled trust in the transmission nodes. Furthermore, the model's versatility allows for simulation with various network performance metrics, thereby offering a comprehensive approach to enhancing network efficiency through multi-objective functions. Comparative analysis with conventional algorithms underscored the superior performance of the proposed model, validating its efficacy as revealed in the aforementioned results.

In summary, this comprehensive study explores the implementation of cognitive routing protocols and energy harvesting-based frameworks within the Internet of Things (IoT) and Cognitive Radio Networks (CRN) for efficient medical data transmission. The first part introduces the novel SR-CHGWO algorithm, demonstrating substantial improvements in node power compared to existing algorithms. The second part focuses on the HCSEHO optimization strategy in a Cognitive Radio Sensor Network (CRSN), showcasing notable performance enhancements, especially in energy harvesting. The final section discusses the D-LBOA optimization mechanism for data transmission in CRN, emphasizing improvements in trust performance and network lifespan. The study underscores the superiority of these proposed models over conventional algorithms, validating their effectiveness through comprehensive simulations and analyses.

CHAPTER 7

FUTURE SCOPE

This thesis presents a complete study and performance evaluation of EH-CRSN from different perspectives. Further, as a part of future research works the following are the few points that can be considered to enhance the performance of Energy Harvesting based CR Networks.

The energy Harvesting model consider for this analysis assumes a linear piece wise model. Practical Non-Linear models can also be used for real time analysis of the system. Further real time data can be used for the simulation of the proposed network and can extended the work based on the amount of data and its impact on the network parameters can be studied. Extend research on optimal cluster head selection by refining multi-objective functions, considering evolving parameters and constraints to enhance the overall efficiency of data transmission. Develop and implement more robust security measures to ensure the confidentiality and integrity of medical data transmitted over the Internet of Medical Things (IoMT). Explore encryption and authentication methods to fortify the security of sensitive healthcare information. Continuous Improvement of Optimization Algorithms: Continuously refine and enhance the optimization algorithms (e.g., SR-CHGWO, HCSEHO, D-LBOA) by incorporating feedback from practical implementations and addressing any identified limitations or challenges.

LIST OF PUBLICATIONS

1. B Naresh Kumar, Jai Sukh Paul Singh. Intelligence-based optimized cognitive radio routing for medical data transmission using IoT[J]. AIMS Electronics and Electrical Engineering, 2022, 6(3): 223-246. doi: 10.3934/electreng.2022014

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3. B. N. Kumar and J. S. P. Singh, "Trust-based Energy Aware Routing Protocol to Improve Network Lifetime in CRNs," 2023 7th International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC), Kirtipur, Nepal, 2023, pp. 307-313, doi: 10.1109/I-SMAC58438.2023.10290348.

4. B. N. Kumar and J. S. P. Singh, "Efficient Optimization Algorithm for IoT-based Cognitive Radio Routing Model with Energy Harvesting for Medical Data Transmission," 2023 International Conference on the Confluence of Advancements in Robotics, Vision and Interdisciplinary Technology Management *(IC-RVITM)*, Bangalore, India, 2023, pp. 1-9, doi: 10.1109/IC-RVITM60032.2023.10435275.

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