Electronics and Electrical Engineering

AIMS Electronics and Electrical Engineering, 6(3): 223–246.
DOI: 10.3934/electreng.2022014
Received: 11 May 2022
Revised: 28 June 2022
Accepted: 06 July 2022
Published: 25 July 2022

http://www.aimspress.com/journal/ElectrEng

Research article

Intelligence-based optimized cognitive radio routing for medical data transmission using IoT

B Naresh Kumar[1,2,]* and Jai Sukh Paul Singh[3,4]

[1] School of Electronics and Electrical Engineering, Lovely Professional University, Phagwara, Panjab, India
[2] Department of ECE, B V Raju Institute of Technology, Narsapur, Telangana, India
[3] School of Electronics and Electrical Engineering, Lovely Professional University, Phagwara, Panjab, India
[4] Department of Research Collaboration, Division of Research and Development, Lovely Professional University, Phagwara, Panjab, India

* **Correspondence:** Email: naresh194u@gmail.com.

Abstract: The Internet of Things (IoT) is considered an effective wireless communication, where the main challenge is to manage energy efficiency, especially in cognitive networks. The data communication protocol is a broadly used approach in a wireless network based IoT. Cognitive Radio (CR) networks are mainly concentrated on battery-powered devices for highly utilizing the data regarding the spectrum and routing allocation, dynamic spectrum access, and spectrum sharing. Data aggregation and clustering are the best solutions for enhancing the energy efficiency of the network. Most researchers have focused on solving the problems related to Cognitive Radio Sensor Networks (CRSNs) in terms of Spectrum allocation, Quality of Service (QoS) optimization, delay reduction, and so on. However, a very small amount of research work has focused on energy restriction problems by using the switching and channel sensing mechanism. As this energy validation is highly challenging due to dependencies on various factors like scheduling priority to the registered users, the data loss rate of unlicensed channels, and the possibilities of accessing licensed channels. Many IoT-based models involve energy-constrained devices and data aggregation along with certain optimization approaches for improving utilization. In this paper, the cognitive radio framework is developed for medical data transmission over the Internet of Medical Things (IoMT) network. The energy-efficient cluster-based data transmission is done through cluster head selection using the hybrid optimization algorithm named Spreading Rate-based Coronavirus Herding-Grey

Wolf Optimization (SR-CHGWO). The network lifetime is improved with a cognitive- routing based on IoT framework to enhance the efficiency of the data transmission through the multi-objective function. This multi-objective function is derived using constraints like energy, throughput, data rate, node power, and outage probability delay of the proposed framework. The simulation experiments show that the developed framework enhances the energy efficiency using the proposed algorithm when compared to the conventional techniques.

Keywords: Internet of Things; Cognitive Radio Sensor Networks; medical data transmission; Spreading Rate-based Coronavirus Herding-Grey Wolf Optimization; cluster head selection; IoT routing

1. Introduction

IoT is used in diverse practical applications and seeks attention from most of the researchers. The number of devices linked to the Internet has exploded because of recent technological breakthroughs. Due to the tremendous increase in the number of internet-connected gadgets (IoT devices), more and more connectivity challenges are arising every day. IoT applications can now be found in a variety of fields, including smart cities, smart transportation, smart health, smart agriculture, and smart industry. As a result, deploying these IoT devices or systems in numerous industries will result in significant cost savings and revenue. Wireless Sensor Networks (WSNs) play an important role in IoT as they are essential for collecting data. However, WSNs bring certain challenges regarding spectral congestion, localization, security, delay, stability, and energy [1]. Researchers are employing various strategies to alleviate the issues associated with the IoT sector as a result of its rapid growth. The allotment of spectrum bands in IoT applications is a key concern.

Due to the large number of IoT devices that require seamless connectivity at all times anywhere, the available spectrum cannot be sufficient because the available spectral bands are overcrowded. Researchers are looking for new spectral bands or new methods that are feasible to provide a seamless connection between the IoT devices. The recent adaptation of Cognitive Radio Networks (CRN) in IoT has shown more remarkable performance than the currently used technologies like Wi-Fi, Wi-Max, Bluetooth, etc. All these networks are static spectrum allocation methods.

Hence, opportunistic methods for Radio Frequency (RF) spectrum access control and management to optimize the finite spectrum resources are emerging as one of the primary difficulties. With the recent unpredicted increase of wireless communication systems, applications and their users limit spectral resources and make the connectivity between their interconnected objects a tedious task. As a result, there is an enormous surge in the need for smart devices that can control and change their transmission settings based on the availability of spectrum resources in spatiotemporal dimensions. [2]. The best candidate technology is called Cognitive Radio (CR), which is described as an adaptive, smart radio and network technology that automatically determines available channels in a wireless spectrum and modifies its transmission parameters to allow more concurrent communications and enhance radio operating behavior. On the other hand, when accessing unlicensed bands, will increase the issues related to coexistence. Hence, IoT devices required supplementary capabilities for overcoming the interference caused by other applications and devices [3]. The medical industry holds much medical data, which has been increasing accordingly. This medical data needs to be transmitted to medical experts for better diagnosis. Further, it is very challenging to design an effective routing protocol in CR with the help of IoT as the IoT nodes and spectrum are heterogeneous and dynamic.

In cognitive technology, patient information in the medical industry can be integrated and made accessible to medical experts all around the world. Different varieties of medical data from various sources have provided enhanced information for decision-making and empowering the medical system. This technology enables medical experts to interpret different kinds of medical information related to the patient's health situation [4]. It also acquires medical data with the help of health monitoring devices and changes them to very useful information for medical experts [5]. In this aspect, cognitive technology supports clinicians in making appropriate decisions by comparing the decisions with the existing information to provide better treatment. In mobile ad-hoc networks, the directional broadcast in each antenna beam is reasonable as it has a more available global control channel. On the other hand, in the CR networks, the accessing of the opportunistic licensed channel is unable to have global channel control for broadcasting the route control messages for the entire antenna beam [6]. Additionally, the directional broadcast antenna beam across diverse non-overlapped licensed channels will cause deafness and multi-channel hidden terminal problems. This most appropriately ensures that cognitive radio networking with opportunistic radio access is considered to be the clearest networking technology for reducing the radio spectrum scarcity problem, which is most probably essential for accommodating the data for many IoT devices. Hence, it is necessary to develop a new cognitive radio framework in IoT for efficient medical data transmission.

1.1. Contributions of the research

The main aims of the suggested medical data transmission model are given as follows.

- To develop an energy-efficient cognitive radio network with a hybrid optimization algorithm for efficiently transmitting medical data without any delay or loss in the transmission with the IoT devices.
- To implement the hybrid optimization algorithm named SR-CHGWO to perform optimal cluster head selection between the source and destination nodes in the cognitive network to make effective medical data transmission.
- To validate the effectiveness of the proposed routing protocol with conventional techniques and analyze the objective constraints for cluster head selection.

1.2. Organization of the work

The rest of the paper is organized as follows. Section 2 describes the existing work and its literature. In section 3, the general architecture of cognitive routing and the proposed routing method are elaborated. In section 4, the suggested SR-CHGWO-based cluster head selection is clearly explained. In section 5, the multi-objective constraints for the cluster head selection are described. In section 6, the results and discussions are given. Section 7 finally concludes the entire research work.

2. Literature survey

2.1. Related works

In 2020, L. Manman et al. [7] suggested a Back Propagation Neural Network-based energy-efficient dynamic clustering approach for IoT applications (BPNN). They processed the information amount depending on power demand by individual clusters using neural networks and Copula theory. The overall energy is optimized based on network requirements, allowing for the most efficient usage of intra-cluster data. In 2020, Wang et al. [8] developed a novel routing protocol to select the ongoing candidates according to the best stopping theory and utilize the network coding for the data transmission among the trusted nodes. Additionally, this designed approach was used for allocating the trusted channel to achieve the expected network gain. Experiments were performed for comparing the efficacy of the proposed one with the conventional protocols in some performances like expected routing cost, average delay and so on.

In 2021, Dhiman and Sharma [9] integrated a cross-layer routing technique in CRSN for maximizing the routing efficiency and tuning the data transfer over reconfigurable networks. With the help of an advanced Spotted Hyena Optimizer (SHO), the hyperparameters were tuned for the machine learning models. The suggested system generated the distributor for performing various tasks like path development, load balance and quarter sensing. The developed technique was inappropriate for the charges and traffic. The results were compared with baseline methods, which revealed the consistent performance of the suggested technique in terms of resources and scalability.

In 2021, A. Mukherjee et al. [10] proposed a dynamic cluster model based on hybrid NN optimization and the Gaussian copula method. The calculation time and energy consumption were both significantly decreased because of this strategy.

To extend the life of WSNs, Kuila, et al. [11] employed a clustering approach based on Particle Swarm Optimization. The cluster formation in this technique has been influenced by two factors: first, the average cluster distance, and second, the lifespan of the gateway. The fitness-function approach is used to calculate the fitness values of each particle in the system, and this fitness value is then used to condition the system's quality. A particle with a higher fitness function value gives the network a better structure.

The authors in [12] have investigated The Cluster Head (CH) identification model for Multi-input Multi-output (MIMO) technology in wireless sensor networks It is based on the theory of linear regression. To localize the location of a CH based on the iterative method for determining the dynamic nodes' positions inside a cluster in intra-cluster cooperative communication, the model uses distributed gradient approach. In [13] the location identification issue of CHs for MIMO sensor networks for ITS applications was addressed. To find CHs for MIMO sensor networks, which can reduce the overall estimate error, they employed BPNN in combination with the distributed gradient drop approach.

In 2021, Gopi Krishnan et al. [14] investigated a novel communication protocol by combining the solutions of energy and delay problems in CRSNs for IoT applications. An evaluation was made with several existing methods using certain comparative measures and found the enhanced performance on the energy consumption and delay. In 2020, Vimal et al. [15] initiated development of a novel heuristic algorithm named "Multi-objective Ant colony optimization (MOACO)" with a deep learning network. Here, the clustering technique was integrated for performing the data utilization and for enhancing the inter-cluster data aggregation. The investigated method extended the network life span to improve green communication using modeling based on artificial intelligence. The validation results showed that the throughput and jamming prediction seemed to be enhanced with the suggested method.

In 2019, Ghose et al. [16] implemented two routing schemes named "Early Sleeping (ES) and Early Data Transmission (EDT)" for reducing the time and energy consumption in the network. The ES method was enabled with decoding and validating the address that made the non-destined devices undergo sleep. The effectiveness of the designed techniques was analyzed with certain simulations along with certain theoretical analyses. In 2018, Anamalamudi et al. [17] developed a combined control channel with the help of a cognitive routing protocol for discovering the channel route using the directional antennas associated with the cognitive networks. The simulation analysis proved that the suggested routing protocol has performed better than other wireless networks.

In 2017, Fayyaz et al. [18] developed a CR for achieving better throughput and continuous associations to acquire consistent communication. The developed CR protocol required less time for computation and performed the data transmission with more throughputs when compared with other protocols. This work also extended the CR technology to solve the practical issues in the IoT to make it applicable and affordable. In 2019, Kumar et al. [19] developed the "Cognitive Data Transmission Method (CDTM)" for monitoring, recording, and transmitting the health data of the patient. Here, cognitive technology was used to effectively monitor and transmit medical data to the healthcare industry. At last, the stochastic prophesy representation was utilized for the prediction of future health status for most of the patients with the present health scenarios. The performance of the suggested routing protocol was assessed and showed accurate prediction with less time required through the bandwidth utilization.

In 2016, Mukherjee et al. [20] addressed the problems of Fusion Centre (FC) based on hierarchical maximum likelihood (HML) clustering for cooperative communication in cognitive radio networks, and the problem of FC positioning was addressed.

2.2. Problem statement

Increasing healthcare data exists in a distributed database available in the cloud, for sharing among medical experts. However, the existing design could not sustain both analysis and processing of the huge quantity of multi-organized healthcare data. Therefore, IoT-based cognitive routing protocols are used for medical data transmission. Some of the existing models are depicted in Table 1. TOT [8] enhances the performance of the data transmission and allows the relay packets to reach rapidly to the target at minimum cost. However, it is highly prone to various kinds of attacks owing to its dynamic spectrum availability. SHANN and SHO [9] benefit in allowing the optimum data transmission at the higher level of the network. But they do not consider the channel imperfection effects as it constraint for updating the routing table. DEDC [14] minimizes energy consumption and enhances communication speed. On the other hand, it does not evaluate based on the hardware implementation and not addressed the accuracy. MOACO [15] improves the lifetime parameters, residual energy, and network lifetime. On the other hand, the analysis with the traditional models is not performed using the energy parameters in terms of jamming attacks. ES and EDT [16] strengthen the transmission and do not allow the re-transmission and secure a slightly higher packet delivery ratio. However, they do not consider the effect of interference levels over the concurrent transmissions under the realistic channel scenarios. CR-AODV [17] achieves satisfying throughput and network energy consumption and reduces nodes. However, it is limited in selecting the optimized energy-efficient end-to-end channel route owing to the cognitive control channel saturation. CR-MAC [18] secures high throughput and transmission energy, but it is prone to hacking and damage to the users. CDTM [19] ensures accurate prediction and reduces the CPU and bandwidth consumption for decreasing the analysis time. However, it is not applicable in the actual healthcare field for examining the practical data. By considering these existing challenges, a new model needs to be developed for medical data transmission using cognitive routing protocols in IoT.

Table 1. Features and challenges of existing cognitive radio routing with IoT for medical data transmission.

Author	Methodology	Features	Challenges
Wang *et al.* [8]	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 [9]	SHO	It benefits in allowing the 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.* [14]	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.* [15]	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.* [16]	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.* [17]	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.* [18]	CR-MAC	It secures high throughput and transmission energy.	It is prone to hacking and damage to the users.
Kumar *et al.* [19]	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.

3. Medical data transmission using intelligent IoT-based cognitive routing

3.1. Cognitive routing in IoT

An end-to-end network provides effective performance as the routing protocol in CR with IoT networks relies on the node energy consumption, end-to-end packet delays, and network throughput. This can be achieved through the "Common Control Channel (CCC)" which is very effective in providing superior end-to-end route discovery and is effective in route maintenance at the time of application in the packet transmission. Moreover, a directional antenna is also introduced for increasing the count of the simultaneous transmissions of non-interfering channels among the cognitive radio networks. This makes several enhancements in the end-to-end throughput over the multi-hop communication network with efficient spatial reuse and for achieving the minimal amount of node power requirements. On the other hand, the IoT application and directional cognitive control are used for attaining enhanced throughput with the reduction in the interferences using the directional antennas. The baseline routing protocols involve Omnidirectional transmission for message exchange between the cognitive control and application data in cognitive-based IoT networks. However, there exists a huge amount of packet loss and there are often failures in the channel route owing to the co-channel interference when processing both the secondary and primary users. The primary users access the frequency from the radio depending on the license and the secondary users do not have a license, but they access the radio frequency without affecting the networks. These users communicate with the base station that acts as a hub collecting the observations and results of spectrum analysis performed by each CR secondary user to avoid interference with the primary networks. The general architecture of the cognitive routing in IoT is shown in Figure 1.

In Figure 1 the primary users are the licensed users, and the secondary users are the unlicensed users who will opportunistically use the resources of the primary user in their absence thereby utilizing the spectrum efficiently by the sensor nodes of the IoT network. The sensor data will be collected by the cluster head of the IoT network and transfer the aggregated data to the base station by utilizing unused spectral bands of the primary network. Each cluster head will be acting as a Cognitive IoMT device to transmit the collected data from the sensor node to the base station. All the cluster heads will form a cognitive radio network.

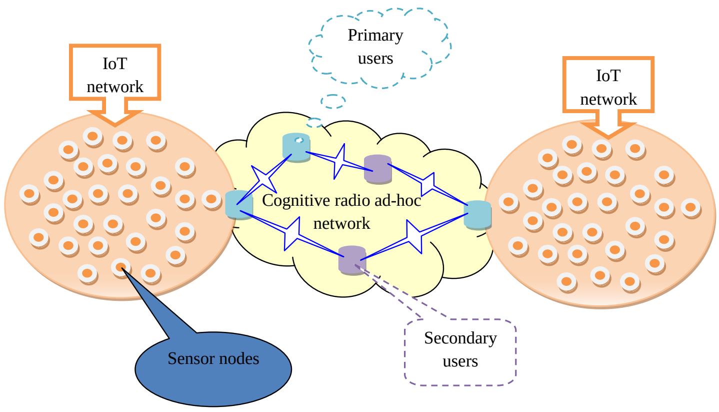


Figure 1. Architectural view of cognitive routing in IoT.

3.2. Proposed Cognitive IoT Routing for medical data transmission

With the increasing applications of wireless devices, users have increased in the wireless networks that enhance internet connectivity. The IoT devices with restricted battery usage and also with delay-sensitive applications make challenges in time-delay limits. It is known that not all the applications of IoT are delay-sensitive which shows it can generate promising results on the multi-hop CRNs based on the energy-aware cognitive radio routing protocols. However, several IoT devices are not dependent on energy-constraints, owing to their independence from battery-powered devices or else because the device battery can be recharged. They can be used with delay-sensitive applications like smart grids. This shows that the delay-efficient cognitive radio routing protocol for supporting these applications like process automation requires a slightly high time consumption. On considering the CRNs, if one device experiences energy depletion, then disconnection may occur in the network, which makes it a less effective network. Hence, an effective cognitive routing protocol is required for solving the existing challenges based on IoT as shown in Figure 2. A new cognitive radio routing framework in IoT is developed for effectively transmitting medical data without any information loss or delay in the network. Here, a hybrid optimization algorithm is developed for performing the optimal cluster head selection to make the efficient transmission of the medical data. Multi-objective constraints are considered for selecting the optimal cluster head using the developed

SR-CHGWO which includes, distance, energy, throughput, data rate, power, outage probability and delay for enhancing the performance of medical data transmission regarding the energy and time consumption of the network. The proposed cognitive radio routing protocol further improves the network efficiency by extending the network lifetime and reducing delay transmission over the IoMT network.

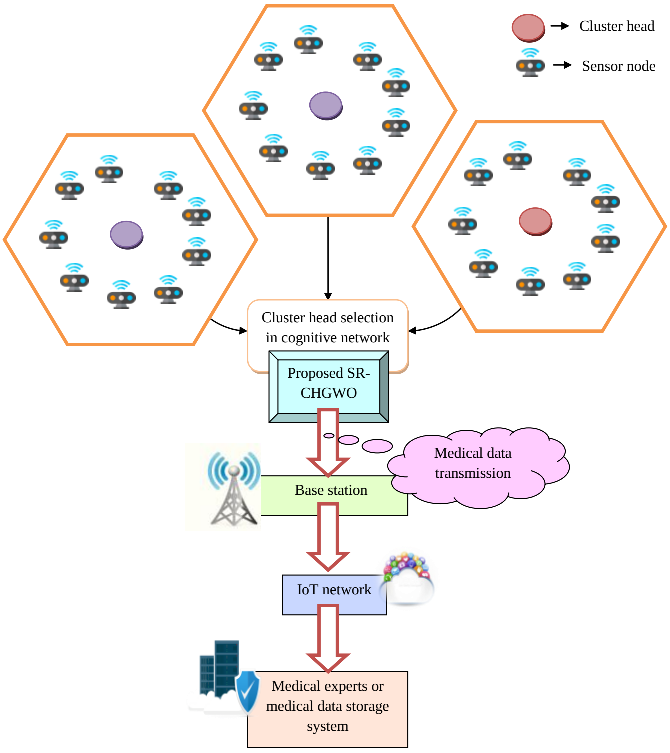


Figure 2. The developed cognitive routing protocol in IoT network.

3.3. Description of medical data taken for transmission

The medical data transmission is performed in the proposed energy-efficient routing protocol by collecting the medical data from three different datasets which are described as follows.

Dataset 1 ("Diabetes Dataset"): The medical data is obtained as information about diabetes disease. This dataset aims to forecast according to the diagnostic measurements for detecting patients with diabetes. Here, the dataset considers female patients under the age of 21 years. It is comprised of instances counting as 768 and attributes counting as more than 8 classes.

Dataset 2 ("Heart Disease Dataset"): It contains 76 attributes, including the predicted attribute, but all published experiments refer to using a subset of 14 of them. The "target" field refers to the presence of heart disease in the patient. It is integer-valued 0 = no disease and 1 = disease.

Dataset 3 ("Indian Liver Patient Records"): The involved medical data is acquired from the liver patient records which comprise 416 liver patients' data and the medical records of 167 patients' without liver diseases. The dataset has classified them into two groups, liver patients and non-liver patients.

4. Proposed SR-CHGWO-based cognitive routing in the medical sector

4.1. Cluster Head selection

Clustering is known to be a significant approach to extending the lifetime of the network in wireless communication. It involves groups of sensor nodes combined to form the clusters and performs the selection of cluster heads with the support of proposed SR-CHGWO algorithm. When the generation of a cluster has occurred, it is assigned a time slot by the cluster head for receiving the messages or data from other nodes. Every cluster head is used for collecting the data from each node in the cluster. If the nodes received all the information, then the cluster transmits the medical data to the base station following the data aggregation. Further, the re-clustering and data transmission will take place in many iterations up to the termination of all the nodes. When the cluster size seems to be smaller than the estimated threshold, the clusters will be combined with the neighboring clusters. Hence, the cluster count gets minimized. Simultaneously, the amount of information also gets reduced when the number of nodes become less in the physical environment. The solution encoding of the cluster selection with the developed SR-CHGWO is depicted in Figure 3.

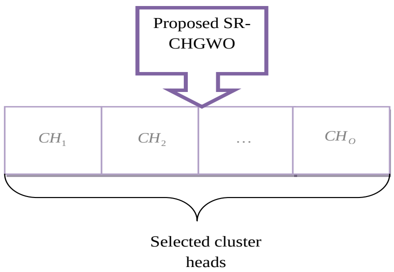


Figure 3. Solution encoding of the cluster head selection with Proposed SR-CHGWO.

4.2. Proposed SR-CHGWO

The medical data transmission with the CR in IoT uses a hybrid form of the algorithm named SR-CHGWO for performing the cluster head selection to effect energy-efficient medical data transmission. Here, GWO is chosen as it minimizes the searching dimension to acquire the convergence rate and also prevents the local optima problem. However, it has poor ability in local searching and low ability to solve the accuracy issues. For handling these existing issues in GWO, it is adopted with the CHIO to implement SR-CHGWO. CHIO can solve the premature convergence problem. The proposed SR-CHGWO enables more efficient performance in the medical data transmission in CR-based IoT applications. In the proposed SR-CHGWO, the spreading rate in the CHIO is computed with the fitness-based concept that is depicted in Eq (1).

$$Spr = \frac{bestfit}{meanfit} \tag{1}$$

Here, the terms mean fit and best fit are indicated by the mean fitness value and best fitness value of the solution. This spreading rate parameter Spr is used for determining the position's update, that is, if the condition (Spr > 0.5) is satisfied, then position update happens with the CHIO or else with the GWO.

CHIO [21] is inspired by observing the herd immunity that acts as the mechanism for stopping the coronavirus pandemic. CHIO is processed with two different parameters such as control and algorithmic parameters. In the control parameters, the rate of transmission of the virus from one individual to another one is termed as spreading rate (basic reproduction rate) Spr, which is computed through Eq (1). Similarly, the max-age MA is computed for determining the status of an affected individual based on their infection age. In the algorithmic parameters, the initially affected cases are denoted by A_0 maximum count of iterations is expressed by Mx_{it} and the population size of herd immunity is expressed by H_{ps}. Here, the solution for the CHIO is acquired according to the three rules given in Eq (2) [21].

$$xx_0^b(it+1) \leftarrow \begin{cases} xx_0^b(it) & rr \geq Spr \\ A\left(xx_0^b(it)\right) & rr < \frac{1}{3} \times Spr \quad //infectedted\ case \\ M\left(xx_0^b(it)\right) & rr < \frac{2}{3} \times Spr \quad //susceptible\ case \\ Q\left(xx_0^b(it)\right) & rr < Spr \quad //immune\ case \end{cases} \tag{2}$$

The term rr indicates the random parameter that lies in the interval $(0,1)$. Here, the term $xx_0^b(it)$ denotes the herd immunity solution with the decision variable as 0 with the solution of b at the current iteration. Here, the status vector S_v is varied for these three cases. In the infected case, the status vector is considered a 1 and the status vector will be 0 in the susceptible cases. In the immune case, it is updated based on the fitness value of the solution. Finally, check the fatality rate to decide the death count and immune count of the individuals. The iteration will be terminated when the herd immunity population is contained with only the immune or susceptible cases without any infected cases.

GWO [22] is developed according to the hunting strategy of the grey wolf which has four main levels of dominant social hierarchy. The hunting behavior of this animal is considered under three phases "tracking, chasing and approaching the prey", "pursuing, encircling and harassing the prey until it stops moving" and "attacks towards the prey". The alpha, beta, omega, and delta are subjected to the levels of wolf, which are correspondingly indicated by α, β, δ, and ω. The grey wolf encircles the prey for its food which is indicated in Eq (3) [22].

$$\vec{Ep} = \left|\vec{Fi} \cdot \vec{Y}u_p(y) - \vec{Y}u(y)\right| \tag{3}$$

$$\vec{Y}u(y+1) = \vec{Y}u_p(y) - \vec{B}t \cdot \vec{Ep} \tag{4}$$

Here, the current iteration is denoted by y, the location of the grey wolf is expressed by $\vec{Y}u$ and the location of prey is expressed by $\vec{Y}u_p$. Certain coefficient vectors are given as $\vec{F}i$ and $\vec{B}t$. Then, the prey location is determined using three positions of the best search agents that are utilized for updating the position of the grey wolf as in Eq (5) [22].

$$\vec{Y}u(y+1) = \frac{\vec{Y}u_1 + \vec{Y}u_2 + \vec{Y}u_3}{3} \tag{5}$$

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

$$\vec{Y}u_3 = \vec{Y}u_\delta - \vec{E}p_3 \cdot \left(\vec{E}p_\delta\right) \tag{6}$$

Here, the term $\vec{Y}u(y+1)$ shows the updated position of the grey wolf. Thus, the best optimal solution is achieved. The pseudo-code of the developed SR-CHGWO is given in Algorithm 1.

Algorithm 1: Proposed SR-CHGWO

```
Population generation along with the involved parameters
Initialize the herd immunity solution in CHIO and best search agents of GWO
determine the best solution
        compute the fitness of every search agent
        compute the spreading rate Spr  as in Eq. (1)
        if (Spr > 0.5)
        update the position using CHIO
              Upgrade the location of the solution according to Eq. (2)
        else
        update the position using the GWO
              Upgrade the location of the solution according to Eq. (5)
        end if
        return the best solution
  end
```

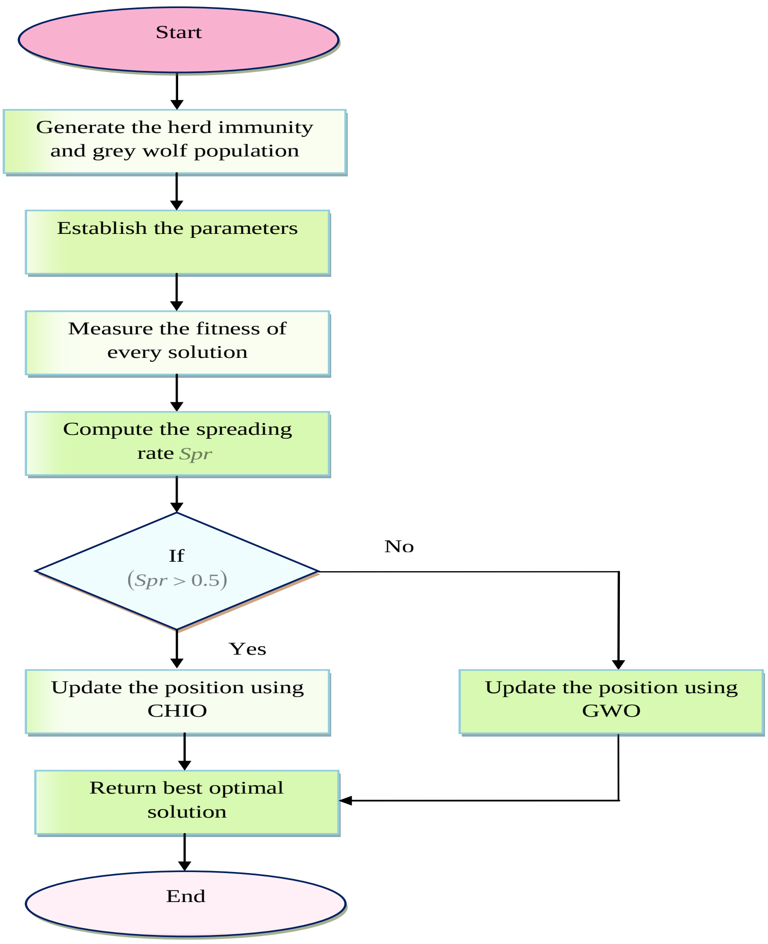


Figure 4. Flow chart of the proposed SR-CHGWO.

5. Derivation of Multi-Objective function for SR-CHGWO-based cognitive routing

5.1. Derived multi-objective function

The proposed CR-based medical data transmission in IoT is performed using the developed SR-CHGWO to determine the shortest path for transmitting the data from the source to the target nodes based on the multi-objective function that include distance, energy, throughput, data rate, power, outage probability, and delay. The objective function Bn of the proposed routing protocol is given in Eq (7).

$$Bn = \underset{\{CH_o\}}{argmin}(f_7) \tag{7}$$

The selected cluster head is indicated by CH_o for the medical data transmission with the support of proposed SR-CHGWO. The objective f_7 is obtained through the following equations. The equations are derived from [11] for cluster head selection.

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

where g_1 and g_2 are the objective constraints

$$f = P * \left(\frac{1}{dis}\right) + (1-P)*\text{en} \tag{8}$$

$$f_1 = Q * f + (1-Q) * \left(\frac{1}{dis}\right) \tag{9}$$

$$f_2 = R * f_1 + (1-R) * (en) \tag{10}$$

$$f_3 = S * f_2 + (1-S) * (thr) \tag{11}$$

$$f_4 = T * f_3 + (1-T) * (datarate) \tag{12}$$

$$f_5 = U * f_4 + (1-U) * (Pwr) \tag{13}$$

$$f_6 = Q_1 * f_5 + (1-Q_1) * \left(\frac{1}{Opr}\right) \tag{14}$$

$$f_7 = Q_2 * f_6 + (1-Q_2) * \left(\frac{1}{delay}\right) \tag{15}$$

The above equations were derived from the multi-objective optimization concepts using minimization or maximization functions. Here, the alpha value P and the beta value Q are 0.2 and the other constraints like gamma R, delta S , omega T, epsilon U, Q_1, and Q_2 are fixed to be 0.1.

5.2. Description of objective constraints

The above-mentioned objective constraints like distance, energy, throughput, data rate, power, outage probability, and delay are explained as follows.

Energy en is acquired through the average energy contained in the alive node at the final experiment as in Eq (16).

$$en = en_{nj} - \left(ei_{nj}^{cs} + ei_{nj}^{sh}\right) \tag{16}$$

Here, the energy used while collecting the data is given as ei_{nj}^{cs}, the energy of any node nj is expressed as en_{nj} , and the energy used while sending the data units is formulated as ei_{nj}^{sh}.

The distance dis among the sources and destination nodes is indicated in Eq (17).

$$dis = \sqrt{\sum_{m=1}^{M}(Ai_{an} - Aj_{an})^2} \tag{17}$$

Here, the source node is denoted as $nd_1 = (Ai_1, Ai_2, \dots Ai_{an})$ and the destination node is depicted as $nd_2 = (Aj_1, Aj_2, \dots, Aj_{an})$.
Throughput thr is the rate of successful data delivery over a communication channel in the cloud network and is given in Eq (18).

$$thr = \frac{\sum(Pi_{sc} * aP_{sz})}{tme} \tag{18}$$

Here, the term aP_{sz} indicates the average packet size, and Pi_{sc} denotes the count of successful packets.
The term $delay$ is computed by considering the transmission and propagation delay over the packets as described in Eq (19).

$$delay = \frac{max\ \sum_{k=1}^{K} SP_k}{nj} \tag{19}$$

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

Data $rate$ is defined as the amount of data transmitted during a specified period over a network. It is the speed at which data is transferred from one device to another.

Transmission power control Pwr is a technical mechanism used within some networking devices to prevent too much unwanted interference between different wireless networks (e.g. the owner's network and the neighbor's network. It is also an essential component in the case of cognitive radio networks deployed in a distributed fashion.

Outage probability Opr is defined as the probability that information rate is less than the required threshold information rate. It is the probability that an outage will occur within a specified time period.

Table 2. Parameters and their descriptions.

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 (2nd best solution)
$M(xx^b_o(it))$	Susceptible case solution (third-best solution)
en	Average energy in the live node
dis	The distance between the source and destination
thr	Throughput
Delay	Propagation delay
Opr	Outage Probability
pwr	Transmission power control

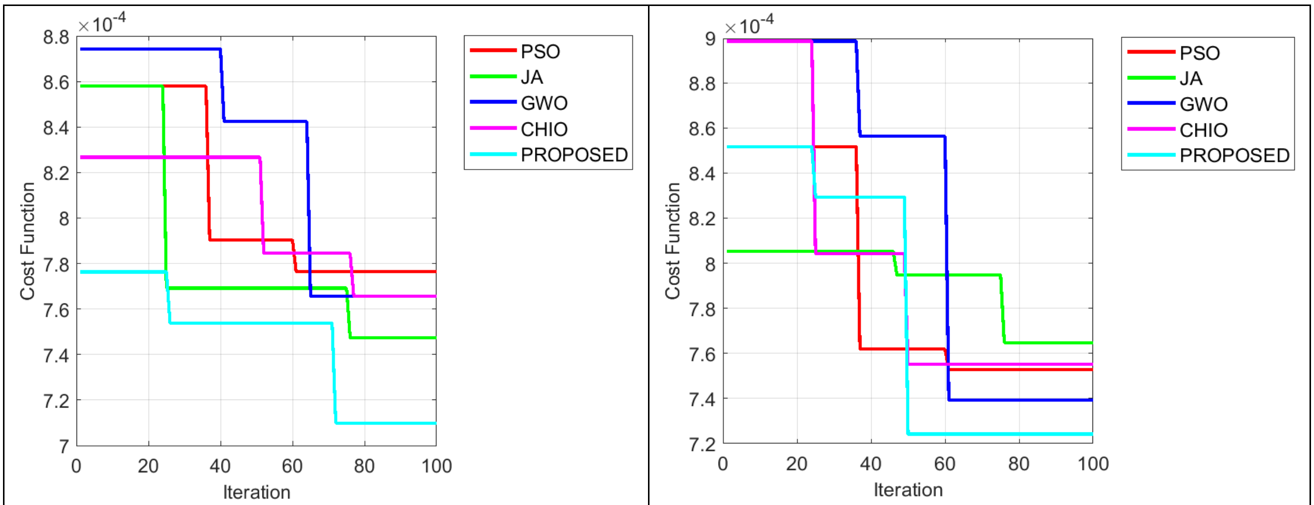
6. Results and discussions

6.1. Simulation setup

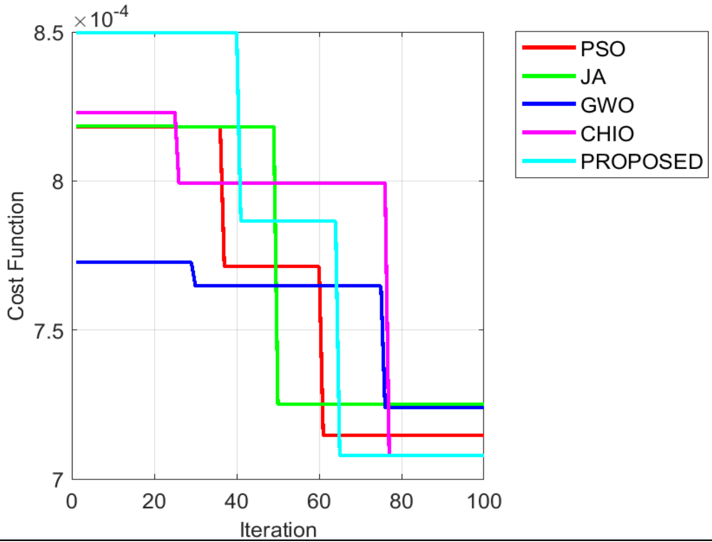
The proposed CR-based medical data transmission network was implemented in a 100 m × 100 m environment. MATLAB 2021a was used. The population size was taken as 10 with 100 iterations. The number of IoMT devices considered for simulation was10. The comparison was made between the proposed SR-CHGWO and existing heuristic algorithms including "Particle Swarm Optimization (PSO), Jaya Algorithm (JAYA), Grey Wolf Optimizer (GWO) [22] and CHIO [21]" for estimating the efficacy of the designed method for effective medical data transmission.

6.2. Dataset 1 analysis with a varying number of nodes

The developed medical data transmission in IoMT with CR technology was analyzed by increasing the iterations up to 100 as shown in Figure 5. On the observation of cost function analysis on three varied nodes, the developed method obtains an improved performance when the number of nodes were count as 50 when compared to the other two-node analysis. Here, the minimum cost function is obtained as the iteration of 40 and it is further decreased to the lowermost cost function when correlated with other algorithms at the 100th iteration. Hence, it is declared that the proposed medical data transmission of IoMT devices with a cognitive routing strategy has an effective performance without any interference.



(a) (b)

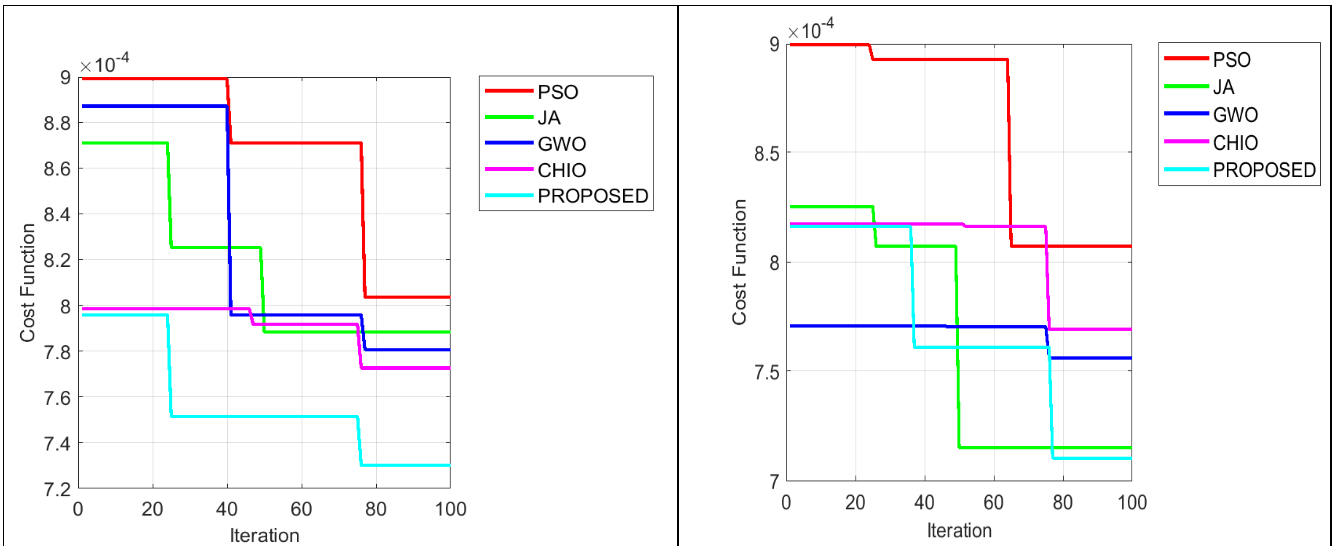


(c)

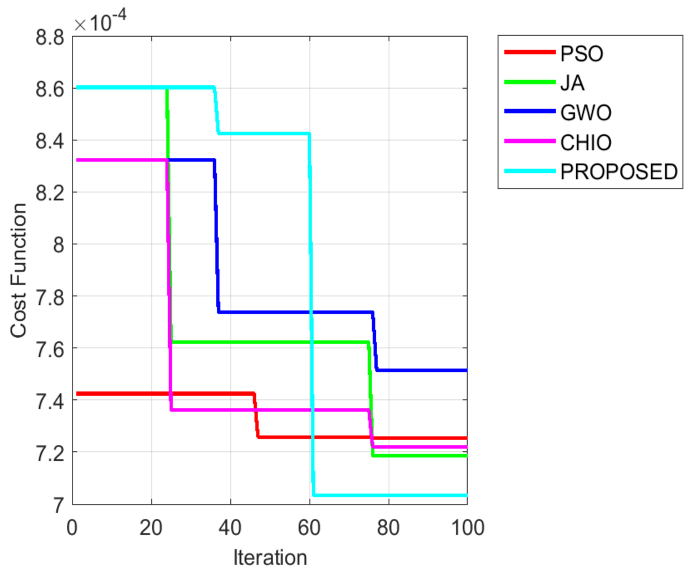
Figure 5. Evaluation of dataset 1 with proposed Cognitive IoT routing for medical data transmission with (a) 50 nodes, (b) 100 nodes and (c) 150 nodes.

6.3. Dataset 2 analysis with a varying number of nodes

The designed cognitive routing protocol was evaluated with the conventional algorithms by changing the number of iterations based on dataset 2 as shown in Figure 6. The proposed SR-CHGWO shows an enhanced performance compared to other algorithms like "PSO, JA, GWO and CHIO", which was revealed through the analysis with 50 nodes. If we consider the 100 nodes for the analysis the proposed model gives excellent performance at the iterations of 80 to 100. This reveals that the suggested method has secured better performance when increasing the number of iterations.



(a) (b)

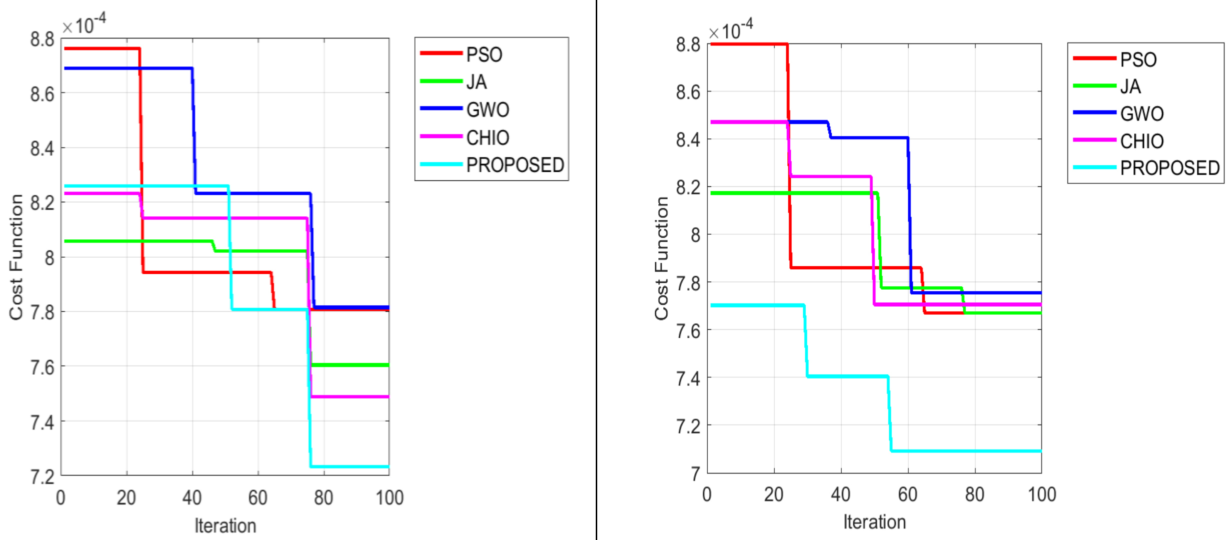


(c)

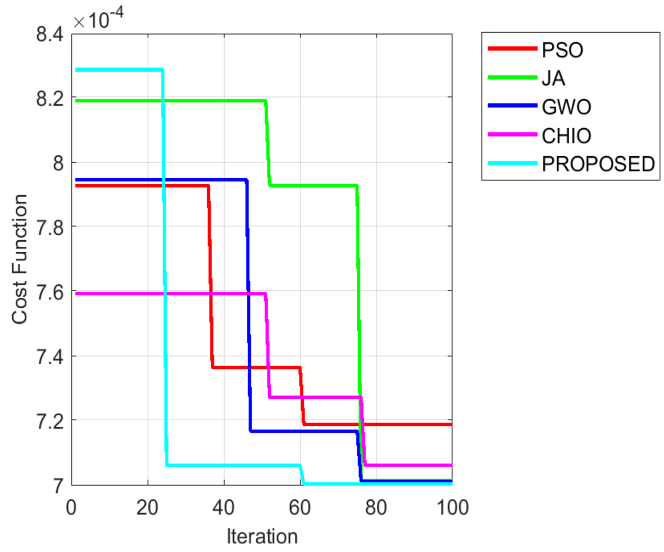
Figure 6. Evaluation of dataset 2 with proposed Cognitive IoT routing for medical data transmission with (a) 50 nodes, (b) 100 nodes and (c) 150 nodes.

6.4. Dataset 3 analysis with a varying number of nodes

The suggested cognitive routing in IoMT for medical data transmission was compared with the baseline algorithms PSO, JA, GWO and CHIO for understanding the effectiveness of the proposed model as shown in Figure 7. The cognitive radio network with 50, 100 and 150 nodes were considered for the analysis and efficient performance was observed for the proposed algorithm where minimum cost function is attained through all the iterations.



(a) (b)

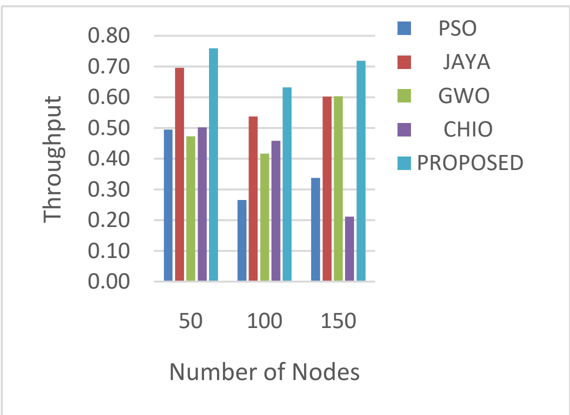


(c)

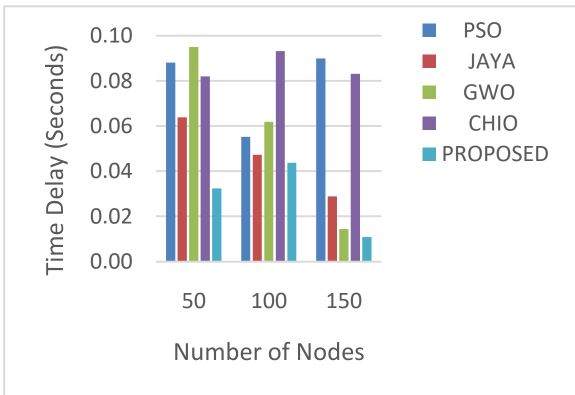
Figure 7. Cost function evaluation on dataset 3 with proposed Cognitive IoT routing for medical data transmission with (a) 50 nodes, (b) 100 nodes and (c) 150 nodes.

6.5. Efficacy evaluation of proposed SR-CHGWO based on dataset 1

The developed SR-CHGWO-based cognitive routing in the IoMT network was analyzed with dataset 1 with respect to various concerns like data rate, node power, time consumption, outage probability and throughput as shown in Figure 8. This analysis table reveals the minimum power consumption in the proposed model which was 6.7%, 4.5%, 7.13%, and 4.3% lower than with PSO, JA, GWO and CHIO, respectively. Also, when observing the time requirements, the proposed model requires much less time for medical data transmission when compared to other algorithms. The computation complexity of the proposed algorithm is also evaluated in terms of the simulation time, and it has been observed that the simulation time is 7.88% lower than with JAYA. Hence, it is revealed that the suggested method has succeeded in achieving better performance than other algorithms.



(a)



(b)

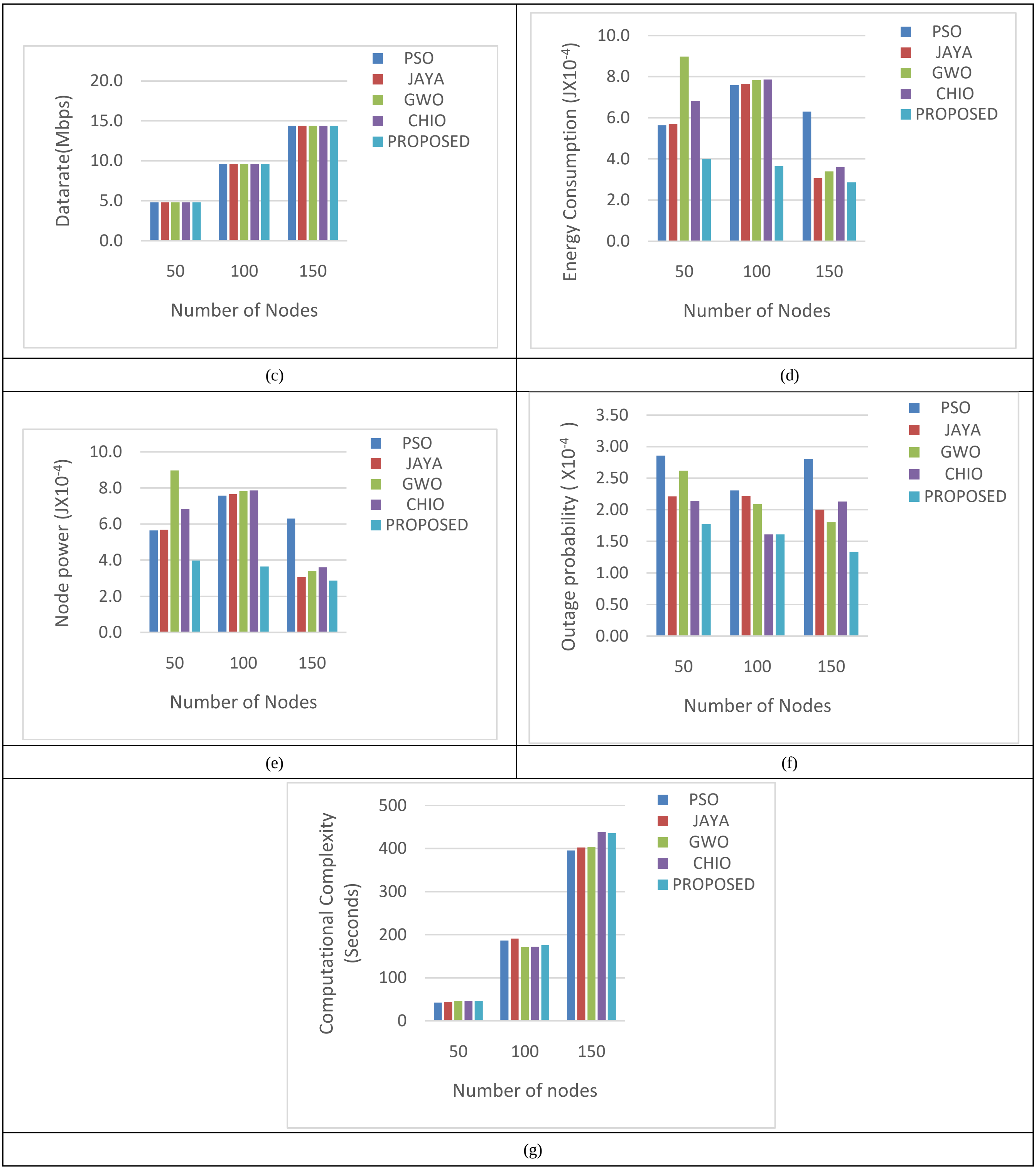
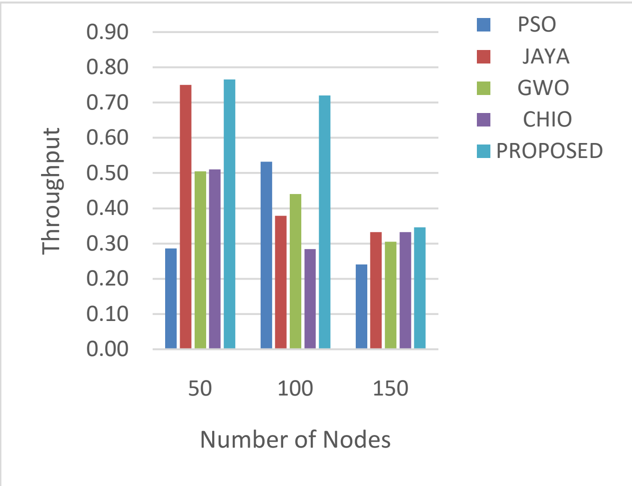


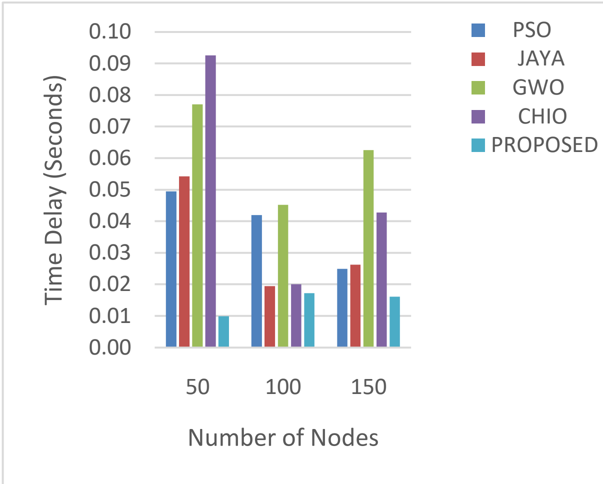
Figure 8. Dataset 1 evaluation on proposed CR-based medical data transmission in IoT using existing algorithms in terms of (a) throughput, (b) time, (c) data rate, (d) energy consumption, (e) node power, (f) outage probability, and (g) computational complexity.

6.6. Efficacy evaluation of proposed SR-CHGWO based on dataset 2

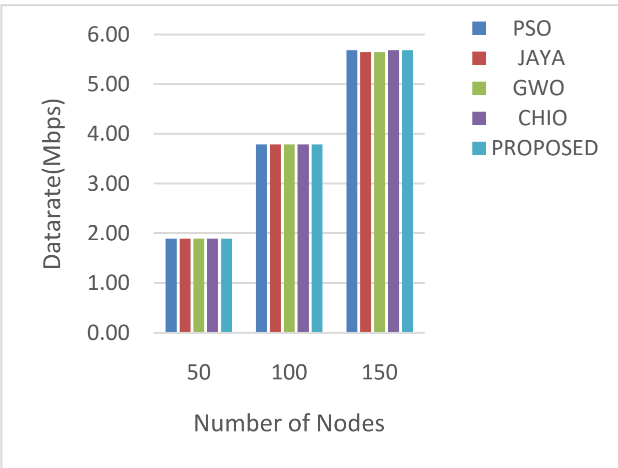
The developed SR-CHGWO-based cognitive routing in the IoMT network was analyzed with dataset 2 with respect to various concerns like data rate, node power, time consumption, outage probability and throughput as shown in Figure 9. Enhancement in throughput was observed with improved values compared to the conventional techniques, by 6.6%, 7.8%, 5.3% and 7.4% for PSO, JA, GWO, and CHIO, respectively. The computational complexity of the proposed algorithm was evaluated and was observed to be 3.11% lower than that of GWO. Similarly, the performance has been enhanced in all the analyses on dataset 2 when compared with existing algorithms.



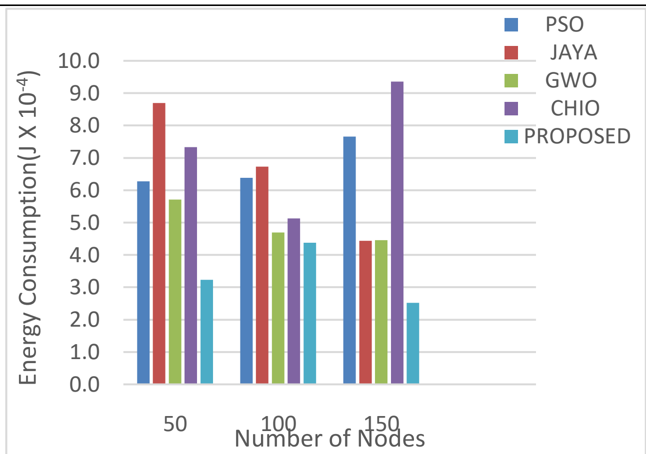
(a)



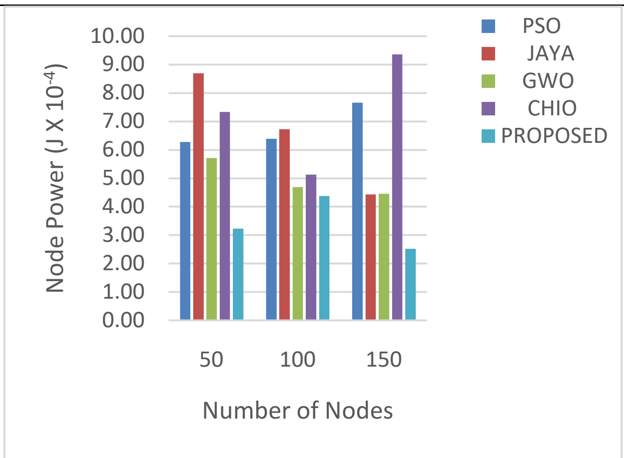
(b)



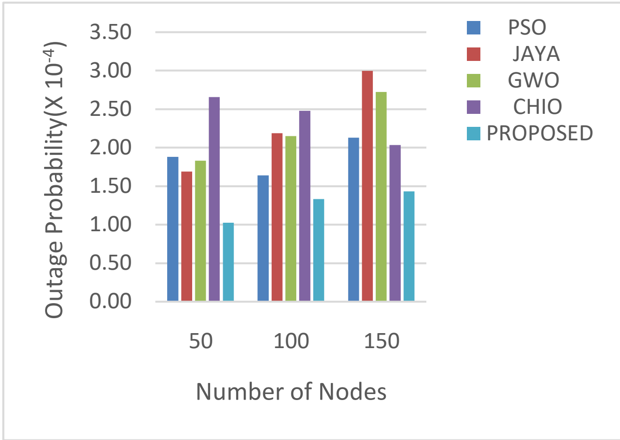
(c)



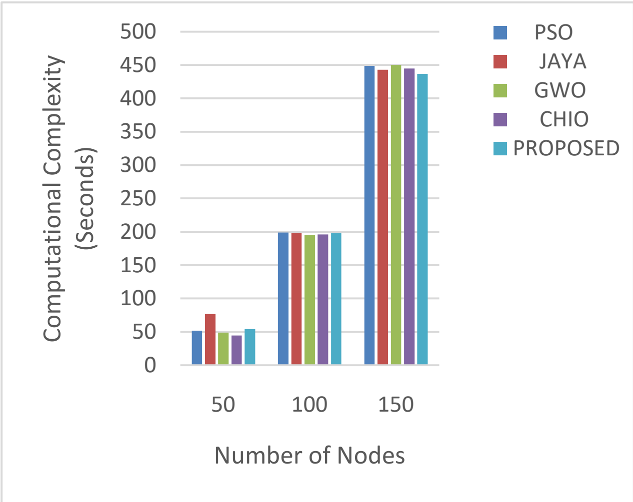
(d)



(e)



(f)

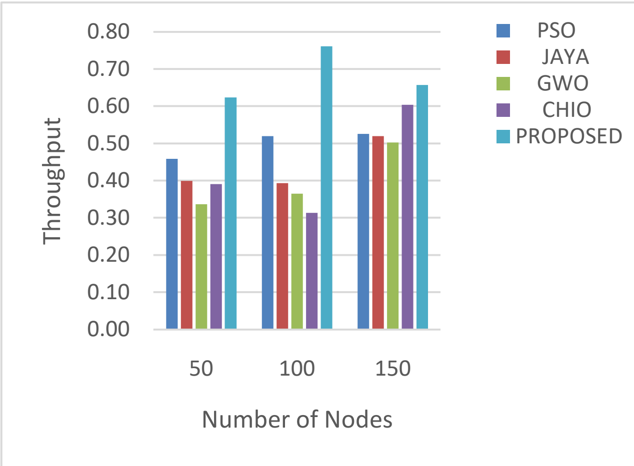


(g)

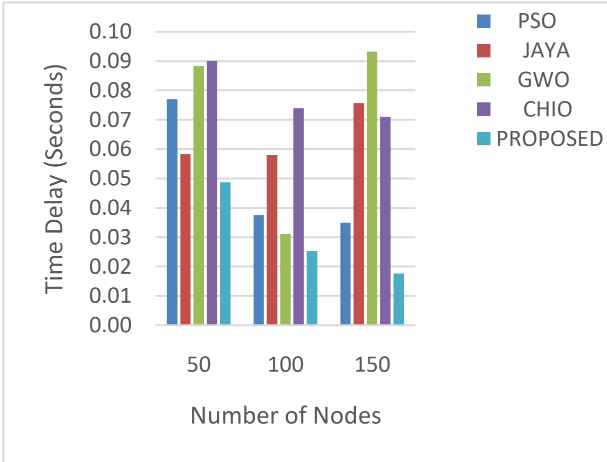
Figure 9. Dataset 2 evaluation of proposed CR-based medical data transmission in IoT using existing algorithms in terms of (a) throughput, (b) time, (c) data rate, (d) energy consumption, (e) node power, (f) outage probability, and (g) computational complexity.

6.7. Efficacy evaluation of proposed SR-CHGWO based on dataset 3

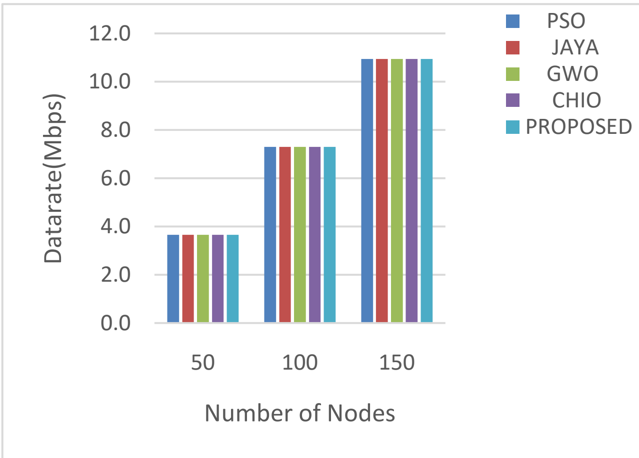
The suggested SR-CHGWO for medical data transmission was evaluated by correspondingly comparing with the existing algorithms PSO, JA, GWO and CHIO based on dataset 3, as shown in Figure 10. The comparison was made between the proposed and conventional algorithms for showcasing the efficiency of the developed routing technique by conducting the analysis with 50, 100 and 150 nodes. The proposed SR-CHGWO secures proficient performance in transmitting the medical data through the IoMT devices, and was observed to be more effective than the conventional algorithms.


Throughput
0.00 0.10 0.20 0.30 0.40 0.50 0.60 0.70 0.80
50 100 150
Number of Nodes
PSO
JAYA
GWO
CHIO
PROPOSED

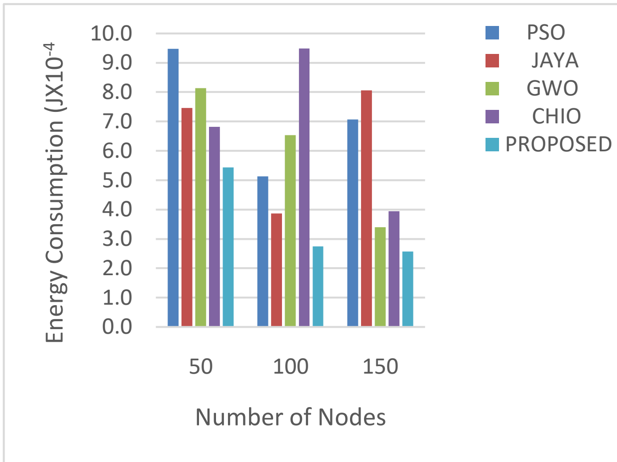
(a)


Time Delay (Seconds)
0.00 0.01 0.02 0.03 0.04 0.05 0.06 0.07 0.08 0.09 0.10
50 100 150
Number of Nodes
PSO
JAYA
GWO
CHIO
PROPOSED

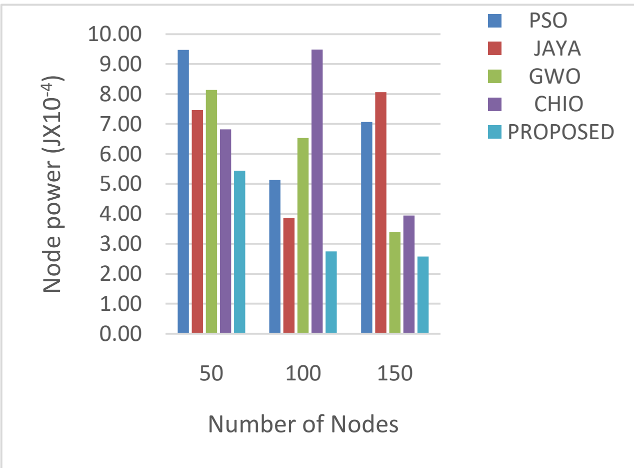
(b)


Datarate(Mbps)
0.0 2.0 4.0 6.0 8.0 10.0 12.0
50 100 150
Number of Nodes
PSO
JAYA
GWO
CHIO
PROPOSED

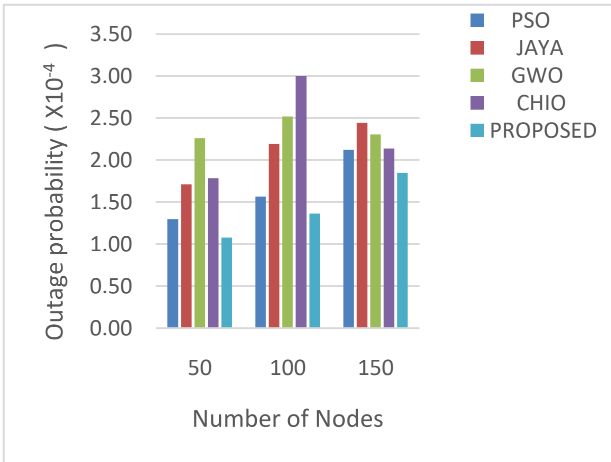
(c)


Energy Consumption (JX10-4
0.0 1.0 2.0 3.0 4.0 5.0 6.0 7.0 8.0 9.0 10.0
50 100 150
Number of Nodes
PSO
JAYA
GWO
CHIO
PROPOSED

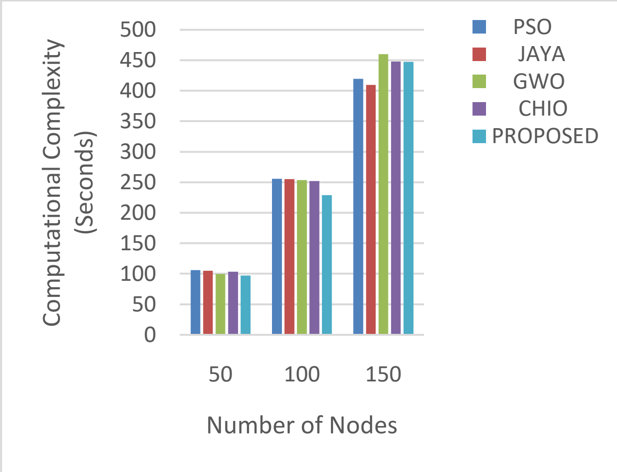
(d)


Node power (JX10-4)
0.00 1.00 2.00 3.00 4.00 5.00 6.00 7.00 8.00 9.00 10.00
50 100 150
Number of Nodes
PSO
JAYA
GWO
CHIO
PROPOSED

(e)


Outage probability (X10-4)
0.00 0.50 1.00 1.50 2.00 2.50 3.00 3.50
50 100 150
Number of Nodes
PSO
JAYA
GWO
CHIO
PROPOSED

(f)



(g)

Figure 10. Dataset 3 evaluation of proposed CR-based medical data transmission in IoT using existing meta-heuristic algorithms in terms of (a) throughput, (b) time, (c) data rate, (d) energy consumption, (e) node power, (f) outage probability and (g) computational complexity.

7. Conclusions

This work has implemented the cognitive routing protocol in IoT for performing effective transmission of medical data by using the suggested SR-CHGWO. The multi-objective constraints were considered for selecting the cluster head with the proposed SR-CHGWO. The constraints used for cluster head selection include distance, energy, throughput, data rate, outage probability and delay. These constraints were utilized for effective data transmission in the IoMT network without any delay and interference. Through the evaluation of the proposed SR-CHGWO, it was confirmed that the proposed routing protocol has secured 42.5%, 27.17%, 33.15%, and 20.3% enhancement compared to PSO, JA, GWO, and CHIO respectively in the analysis of node power. Therefore, it has been shown that effective medical data transmission through the cognitive routing in IoT was observed through the proposed SR-CHGWO. The simulation results also indicate that the computational complexity of the proposed algorithm outperforms when compared with conventional optimization methods.

Conflict of interest

There is no conflict of interest of any author in any form.

References

1. Yuan B, Lin C, Zhao H, et al. (2020) Secure Data Transportation with Software-Defined Networking and k-n Secret Sharing for High-Confidence IoT Services. IEEE Internet Things 7: 7967–7981. https://doi.org/10.1109/JIOT.2020.2993587

2. Awin FA, Alginahi YM, Abdel-Raheem E, et al. (2019) Technical Issues on Cognitive Radio-Based Internet of Things Systems: A Survey. IEEE Access 7: 97887–97908. https://doi.org/10.1109/ACCESS.2019.2929915
3. Fang D, Qian Y, Hu RQ (2020) A Flexible and Efficient Authentication and Secure Data Transmission Scheme for IoT Applications. IEEE Internet Things 7: 3474–3484. https://doi.org/10.1109/JIOT.2020.2970974
4. Zhong X, Li L, Zhang Y, et al. (2020) OODT: Obstacle Aware Opportunistic Data Transmission for Cognitive Radio Ad Hoc Networks. IEEE T Commun 68: 3654–3666. https://doi.org/10.1109/TCOMM.2020.2979976
5. Inagaki Y, Shinkuma R, Sato T, et al. (2019) Prioritization of Mobile IoT Data Transmission Based on Data Importance Extracted From Machine Learning Model. IEEE Access 7: 93611–93620. https://doi.org/10.1109/ACCESS.2019.2928216
6. Zhang K, Leng S, Peng X, et al. (2019) Artificial Intelligence Inspired Transmission Scheduling in Cognitive Vehicular Communications and Networks. IEEE Internet Things 6: 1987–1997. https://doi.org/10.1109/JIOT.2018.2872013
7. Manman L, Xin Q, Goswami P, et al. (2020) Energy-Efficient Dynamic Clustering for IoT Applications: A Neural Network Approach. 2020 IEEE Eighth International Conference on Communications and Networking (ComNet), 1–7. https://doi.org/10.1109/ComNet47917.2020.9306092
8. Wang X, Zhong X, Li L, et al. (2020) TOT: Trust aware opportunistic transmission in cognitive radio Social Internet of Things. Comput Commun 162: 1–11. https://doi.org/10.1016/j.comcom.2020.08.007
9. Dhiman G, Sharma R (2021) SHANN: an IoT and machine-learning-assisted edge cross-layered routing protocol using spotted hyena optimizer. Complex Intell Syst, 1–9. https://doi.org/10.1007/s40747-021-00578-5
10. Mukherjee A, Jain DK, Yang L (2021) On-Demand Efficient Clustering for Next Generation IoT Applications: A Hybrid NN Approach. IEEE Sens J 21: 25457–25464. https://doi.org/10.1109/JSEN.2020.3026647
11. Kuila P, Jana PK (2020) Energy efficient clustering and routing algorithms for wireless sensor networks: Particle swarm optimization approach. Eng Appl Artif Intel 33: 127–140. https://doi.org/10.1016/j.engappai.2014.04.009
12. Mukherjee A, Goswami P, Yan Z, et al. (2020) Distributed gradient descent based cluster head identification in MIMO sensor networks. Optik 204: 164185. https://doi.org/10.1016/j.ijleo.2020.164185
13. Mukherjee A, Jain DK, Goswami P, et al. (2020) Back Propagation Neural Network Based Cluster Head Identification in MIMO Sensor Networks for Intelligent Transportation Systems. IEEE Access 8: 28524–28532. https://doi.org/10.1109/ACCESS.2020.2971969
14. Gopikrishnan S, Priakanth P, Srivastava G (2021) DEDC: Sustainable data communication for cognitive radio sensors in the Internet of Things. Sustainable Computing: Informatics and Systems 29: 100471. https://doi.org/10.1016/j.suscom.2020.100471
15. Vimal S, Khari M, Crespo RG, et al. (2020) Energy enhancement using Multiobjective Ant colony optimization with Double Q learning algorithm for IoT based cognitive radio networks. Comput Commun 154: 481–490. https://doi.org/10.1016/j.comcom.2020.03.004
16. Ghose D, Frøytlog A, Li FY (2019) Enabling early sleeping and early data transmission in wake-up radio-enabled IoT networks. Comput Networks 153: 132–144. https://doi.org/10.1016/j.comnet.2019.03.002

17. Anamalamudi S, Sangi AR, Alkatheiri M, et al. (2018) AODV routing protocol for Cognitive radio access based Internet of Things (IoT). Futur Gener Comput Syst 83: 228–238. https://doi.org/10.1016/j.future.2017.12.060
18. Qureshi FF, Iqbal R, Asghar MN (2017) Energy-efficient wireless communication technique based on Cognitive Radio for Internet of Things. J Netw Comput Appl 89: 14–25. https://doi.org/10.1016/j.jnca.2017.01.003
19. Kumar MA, Vimala R, Britto KRA (2019) A cognitive technology-based healthcare monitoring system and medical data transmission. Meas J Int Meas Confed 146: 322–332. https://doi.org/10.1016/j.measurement.2019.03.017
20. Mukherjee A, Goswami P, Datta A (2016) HML-Based Smart Positioning of Fusion Center for Cooperative Communication in Cognitive Radio Networks. IEEE Commun Lett 20: 2261–2263. https://doi.org/10.1109/LCOMM.2016.2602266
21. Al-Betar MA, Alyasseri ZAA, Awadallah MA, et al. (2021) Coronavirus herd immunity optimizer (CHIO). Neural Comput Appl 33: 5011–5042. https://doi.org/10.1007/s00521-020-05296-6
22. Mirjalili S, Mirjalili SM, Lewis A (2014) Grey Wolf Optimizer. Adv Eng Softw 69: 46–61. https://doi.org/10.1016/j.advengsoft.2013.12.007