

Research Article

Multiobjectives for Optimal Geographic Routing in IoT Health Care System

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In numerous internet of things (IoT) appliances, messages might require to be distributed to certain specified nodes or objects with the multicast transmission. “The multicast routing protocol can be divided into nongeographic based and geographic based.” As locations of device are roughly extracted by GPS devices, geographic-oriented multicast routing schemes were chosen, because it induces lesser overheads. Nevertheless, the extant geographic-oriented routing models are found to have particular disadvantages. After the advent of the IoT systems for remote healthcare, medical services can be rapidly provided to patients in rural areas. The IoT network encapsulates flexible sensors in the environment to collect environmental information. This gathered sensor information is sent to the nursing stations for timely medical assistance. The IoT network is wireless, which leads to security breaches. Therefore, there is a necessity to have a secured data transmission in the context of healthcare. Hence, this study intends to propose a novel optimal route selection model in IoT healthcare by deploying optimized ANFIS. Here, the optimal routes for medical data are selected using a new self-adaptive jellyfish search optimizer (SA-JSO) that is the enhanced edition of the extant JSO model. Accordingly, the optimal route selection for medical data is performed under the consideration of “energy, distance, delay, overhead, trust, quality of service (QoS), and security (high risk, low risk, and medium risk).” In the end, the performances of adopted work are compared and proved over other extant schemes.

1. Introduction

The WSNs are introduced in IoT and act a significant role to give a wider range of appliances via sensors, like environmental monitoring, smart homes, traffic supervision, and smart grids [1]. A WSN includes sinks/receivers and various distributed SNs that collaboratively gather and convey data to carry out various missions [2]. Being built on WSNs, offering consistent data deliverance is generally expected for IoT-oriented appliances. This appliance needs WSNs to offer reliable data deliverance that is considered as the crucial aspect of data transmission. Nevertheless, depending upon the diverse wireless media, WSNs are vulnerable to signal fading or interferences that might considerably reduce the QoS [3–5]. As a result, supporting consistent data deliverance turns out to be a demanding crisis in WSNs.

Recently, the IoT networks provide a lot of advantages in the medical field for providing timely assistance to patients even during the pandemic period. In healthcare, the IoT and cloud resources are wholly utilized, and hence, they are said to be the fundamental aspects of the healthcare context [6]. In between the computational resource, medical equipment, and medical data transmissions from the cloud environment to the cloud computing, the connection is supported by the standard protocols in the cloud environment. Since the cloud platform is open access, there is a huge chance for security breaches to take place. Therefore, there is a necessity to develop an efficient and secured data routing model for reliable data transmissions.

In recent times, a proficient method to meet the conditions of data reliability is deploying (opportunistic) geographic routing that does not portray the routing paths before the transmission of data [7]. In comparing over

multipath routing, geographic routing proffers enhanced performances since no further interferences or signal contentions subsist among nodes [8]. Being a conventional routing model, geographic routing was a striking option regarding the dynamic wireless link, as it does not require maintaining routes from source to sinks [9].

Thereby, the amalgamation of “opportunistic routing and geographic routing is known as geographic opportunistic routing” [10, 11]. Conventional “geographic opportunistic routing” models achieved higher reliability over wireless links. Nevertheless, they endure from DoS attacks [12]. Malevolent attackers might consciously transmit a larger count of illogical data, intending to misuse the resources and to interrupt the normal functions of the network. The IoT, smart sensors, and mobile wearable devices are assisting in the development of healthcare systems that are more pervasive, smarter, faster, and easier to use. Security, on the other hand, is a big worry for the IoT, with access control being one of the major issues. With these systems increasing scale and presence, a crucial concern is how to administer policies in a scalable and adaptable manner. Table 1 describes the abbreviations used in this study.

The major contributions of the adopted methodology are given below:

- (i) An optimized ANFIS system is deployed to select the most optimal routes for data transmission in the context of healthcare.
- (ii) A new self-adaptive jellyfish search model is introduced for optimizing the membership function of ANFIS.

The remaining of this study is arranged as follows: the second section reviews this topic. Section 3 tells about the system model of the developed EEG protocol. Sections 4 and 5 depict about description of multiobjective and optimized ANFIS for data routing via the SA-JSO model. In addition, Section 6 portrays about the deployed steps of the proposed EEG routing protocol. The results and conclusions are given in Sections 7 and 8.

2. Literature Review

2.1. Related Works. In 2017, Huang et al. [13] proposed an EMGR for achieving EER. EMGR employed an “energy-aware multicast tree,” created by source and destination nodes depending upon the energy, for guiding multicast message deliverance. Accordingly, the nodes were adaptively selected for conserving energy. Simulated and analytic resultants demonstrated that the developed model achieved enhanced performances regarding lower complexity, energy utilization, and overhead.

In 2020, Naghibi and Hamid et al. [14] suggested a technique for dividing the network into certain cells in a geographic way and applied 2 mobile sinks for collecting the information sensed by cell nodes. Depending upon the communiqué among mobile sinks and cells, the cells were separated into 2 classes: “SCCs and MCCs.” When sinks were motionless, SCCs transmit data to sinks in a direct manner; however, MCCs applied the adopted EGRPM model to transmit data to sinks.

In 2020, Hameed et al. [4] proposed an EEG routing model for focusing upon energy utilization and throughput of SNs. The adopted model applied the MSE approach to resolving the sensor localization issue. In addition, routing overhead was minimized by limiting the SN to sustain single neighbor data. The adopted model reduced the energy holes in the network by efficiently evaluating the energy utilization amid SNs.

In 2019, Lyu et al. [15] proposed a SelGOR model for defending against the DoS attack and for satisfying the needs of reliability and authenticity in WSNs. By examining SSI, SelGOR leveraged an SSI-oriented trust scheme for improving the effectiveness of data freedom. Moreover, SelGOR ensured data reliability by generating an entropy-oriented model and was capable of isolating DoS attackers and reducing the cost.

In 2021, Banyal et al. [16] have suggested a new method for segmenting the network topology depending upon the node’s characteristics. This model was accomplished by means of “intelligent transmission.” The HiLSeR’s suggested model was deployed for packet routing. For “topology sectionalization and routing decision-making, hierarchical learning, a multidimensional data conduct-oriented soft clustering paradigm,” was deployed. By performing experimentation, the efficiency of the proposed model was evaluated over other models. For demonstrating the enhanced efficiency, diverse parameters like “Energy Unit per Message, Dead node Percentage, Overhead Ratio, Average Latency, and Success Ratio” were computed.

In 2019, Thangaramya et al. [17] suggested a novel “Neuro-Fuzzy Rule-Based Cluster Formation and Routing Protocol” for proficient routing of data in IoT-oriented WSN appliances. The adopted scheme has provided considerably superior network efficiency regarding “energy consumption, packet distribution ratio, latency, and network life span,” which was proved to form the outcomes.

In 2021, Pingale and Shinde [18] have suggested a novel routing scheme for optimizing network lifetime by means of the SFG model. The projected “SFG algorithm” had elected the most excellent routes by merging the SFO and GWO schemes. The simulation of IoT initially appeared, along with the execution of multipath routing in IoT. The SFG model has chosen the optimal routes among the multipath obtainable for routing depending upon “context awareness, network lifetime, residual energy, trust, and latency.”

In 2019, Dhumane & Prasad [19] have adopted a “multiobjective FGSA” for electing the optimal CH in an IoT network for EER protocol. The EER in IoT was attained by exploiting FGSA to find out the finest CH. The CH node in MOFGSA was selected depending upon the fitness appraisal of numerous criteria, together with “distance, latency, connection lifetime, and energy.” MATLAB execution was used to assess the simulated outcomes.

2.2. Review. Table 2 shows the review on EEG in IoT-WSN. Initially, EMGR was implemented, which provides high PDR, less overhead, and less complexity; however, wastage of resources should be concerned more. The uses of the

TABLE 1: Nomenclature.

Abbreviation	Description
ANFIS	Adaptive neuro-fuzzy inference system
DoS	Denial of service
EMGR	Energy-efficient multicast geographic routing protocol
EER	Energy-efficient routing
EEG	Energy-efficient geographic
FGSA	Fractional gravitational search algorithm
GPS	Global positioning system
GWO	Gray wolf optimizer
IoT	Internet of things
MOFGSA	Multiobjective FGSA
MCCs	Multihop communication cells
MSE	Mean square error
PDR	Packet delivery ratio
SFG	Sunflower-based GWO
SNs	Sensor nodes
SelGOR	Selective authentication-based geographic opportunistic routing
SSI	Statistic state information
SCCs	Single-hop communication cells
SA-JSO	Self-adaptive jellyfish search optimizer
SFO	Sun flower optimization
QoS	Quality of service
WSN	Wireless sensor network

TABLE 2: Review on conventional routing protocol in WSN.

Ref. no.	Proposed model	Pros	Cons
1	EMGR	(i) High PDR (ii) Minimal overhead (iii) Less complexity	(i) Wastage of resources should be concerned more
2	EGRPM	(i) Maximizes life span (ii) Minimizes delay	(i) No consideration of overhead
3	ECMSE	(i) Higher energy utilization (ii) Improved throughput (iii) Higher PDR	(i) Network interference issues are not deliberated
4	SelGOR	(i) High reliability (ii) Lower computational cost	(i) Delay performance is not good
5	HiLSeR	(i) High throughput (ii) Enhances PDR	(i) Low PDR (ii) High end-to-end delay.
6	“Neuro-Fuzzy Rule-Based Cluster Formation and Routing Protocol”	(i) Higher energy utilization (ii) Improved network life span (iii) Higher PDR	(i) High computational complexity (ii) Higher delay (iii) Higher end-to-end delay
7	SFG	(i) Reducing data overflow (ii) Lower bandwidth usage	(i) Less convergence rate
8	FGSA	(i) Increased residual energy (ii) Maximum network energy	(i) Lower count of alive nodes

EGRPM algorithm are to have a higher life span and lower delay, but the overhead is high. Furthermore, the ECMSE model was implemented, which enhanced PDR and improved throughput. However, network interference issues are not deliberated. Similarly, the use of SelGOR resulted in lower computational cost and high reliability. However, delayed performance is not good. The uses of the HiLSeR algorithm are to have higher network energy, maximum

alive nodes, lower latency, and lower traffic volume, but the PDR is lower. Furthermore, in [17], an efficient distance-dependent “Neuro-Fuzzy Rule-Based Cluster Formation and Routing Protocol” was implemented, which expanded network lifetime and improved PDR. However, the delay is higher and the complexity is also high. In addition, the SFG algorithm is introduced, which has a reduced number of dead nodes, higher latency, and prolonged network life span.

In addition, the convergence rate is smaller, and the run time is longer. The FGSA algorithm is proposed, which offers increased energy performance, higher network throughput, less energy usage, and maximum network life; however, it requires “extending the EER protocols in WSNs to mobile networks.”

3. System Model of Developed IoT Protocol

In 1987, the first healthcare model was developed in the Picker Institute by the Picker/Commonwealth program. This has paved the way for the development of the patient-centered care services (PCCs) that are being commonly utilized on these days. The major intention behind the PCCs is to provide medical needs to the needy. After the advent of wearable sensors, healthcare services based on IoT networks are gaining huge attention among the research industry. In the normal IoT-based data transmission, the data from the source (patient) to the destination (healthcare center) take place via the lowest hop count and the shortest distance. Even though this model ensures link quality and reliable transmission, the delay in the data transmission became an unavoidable issue. This leads to delay medical services, and hence, the network became less reliable. Moreover, the IoT being battery-powered devices required huge costs for initialization and training. On the other hand, the unauthorized or hacker IoT nodes might hack the sensitive medical data during the data transmission, and they might make modifications to it. As a result, the precise life of the patient might be jeopardized. Therefore, there is a necessary route to secure the medical data from source to destination via the IoTs.

4. Deployed Steps of Proposed Medical Data Routing Protocol: An Overview

The optimal data routing for routing the medical data amid the set of “source node(S) and destination node (D)” with minimal energy utilization is said to be a major challenge in IoT-WSN. The adopted scheme attempted to triumph over this confrontation by developing a novel EEG routing model. The process taking place in the developed work is as follows:

- (i) The adopted scheme develops a novel medical data routing model depending upon sixfold objective functions (energy, distance, delay, overhead, QoS, and trust).
- (ii) Throughout medical data routing, the majority of optimal routes are chosen by optimized ANFIS, wherein the membership functions are optimized.
- (iii) The optimal route is selected via the SA-JSO model that considers multiobjective functions. The architecture of this work is exposed in Figure 1.

4.1. An Illustration. The architectural representation of the IoT healthcare system is manifested in Figure 2. The model encapsulates the WBANs and a broader telemedicine

system. This model serves hundreds or thousands of individual users.

Let there be two COVID-19 patients *User 1 and User 2*, who have been admitted to a remote healthcare location away from the hospital. Since it is being an epidemic situation, there are not enough medical resources. Therefore, the patients *User 1 and User 2* need to be continuously monitored by the doctors. These patients are embedded with numerous body sensor nodes in the user’s belt, an ankle, a knee, or the trunk for monitoring their heart rate, blood pressure, and oxygen saturation as well. Each of the nodes is capable of undergoing operations such as “sampling, processing, and communication.” The coordinator (C), who has greater energy and computing power, coordinates the whole network on one individual for each user. It gathers data from sensor nodes located on or within the human body. There is no personal server, such as a PDA or a PC, in this IoT healthcare system. It has the potential to lower each user’s spending. Using multiple hop routing, the gathered data of the coordinator is sent to the access gateway (AG) via other coordinators. The multihop routing protocol is utilized for safe communication between IoT devices. Before building a new network or integrating an existing one, the routing protocol allows IoT devices to authenticate. To improve the security of the communication, multilayer parameters are used for authentication. AG may be connected to a hospital server and a wired or wireless network appliance. To synchronize nodes in the network, the AG and coordinators send out periodic beacon packets. The AG also uses the internet to send the data to the medical server. If a user leaves the communication range (i.e., there is no other user nearby), the coordinator begins locally buffering data. The route link is restored when the user returns. Sensor and event data are automatically uploaded by the coordinator. The localization strategy is utilized since the users’ location information is also important in the IoT healthcare system. There are a few reference nodes (RNs) in the vicinity. They are GPS enabled or preprogrammed with the location of nodes. The signal of RNs and the localization method may be used by coordinators to determine their own positions. As depicted in the projected model, the secured path for data transmission takes based on the defined sixfold objective: highest energy, lowest distance, lowest delay, lowest overhead, highest QoS, and highest trust. A prominent role is being played by these parameters during the selection of the most prominent next-hop nodes for data transmission. The optimized ANFIS model finds the majority of optimal routes, and among the available next-hop paths that satisfy the sixfold objectives (i.e., highest energy, lowest distance, lowest delay, lowest overhead, highest QoS, and highest trust), the optimal one is selected with the newly projected SA-JSO model.

The medical services can be provided when the medical professional has analyzed the patient’s information. The medical server keeps track of the users’ personal information and their health data. The uncomplicated ailment is diagnosed by an expert method. If the patient’s condition is critical, hospital specialists can determine a diagnosis based on the patient’s information. Experts from all around the

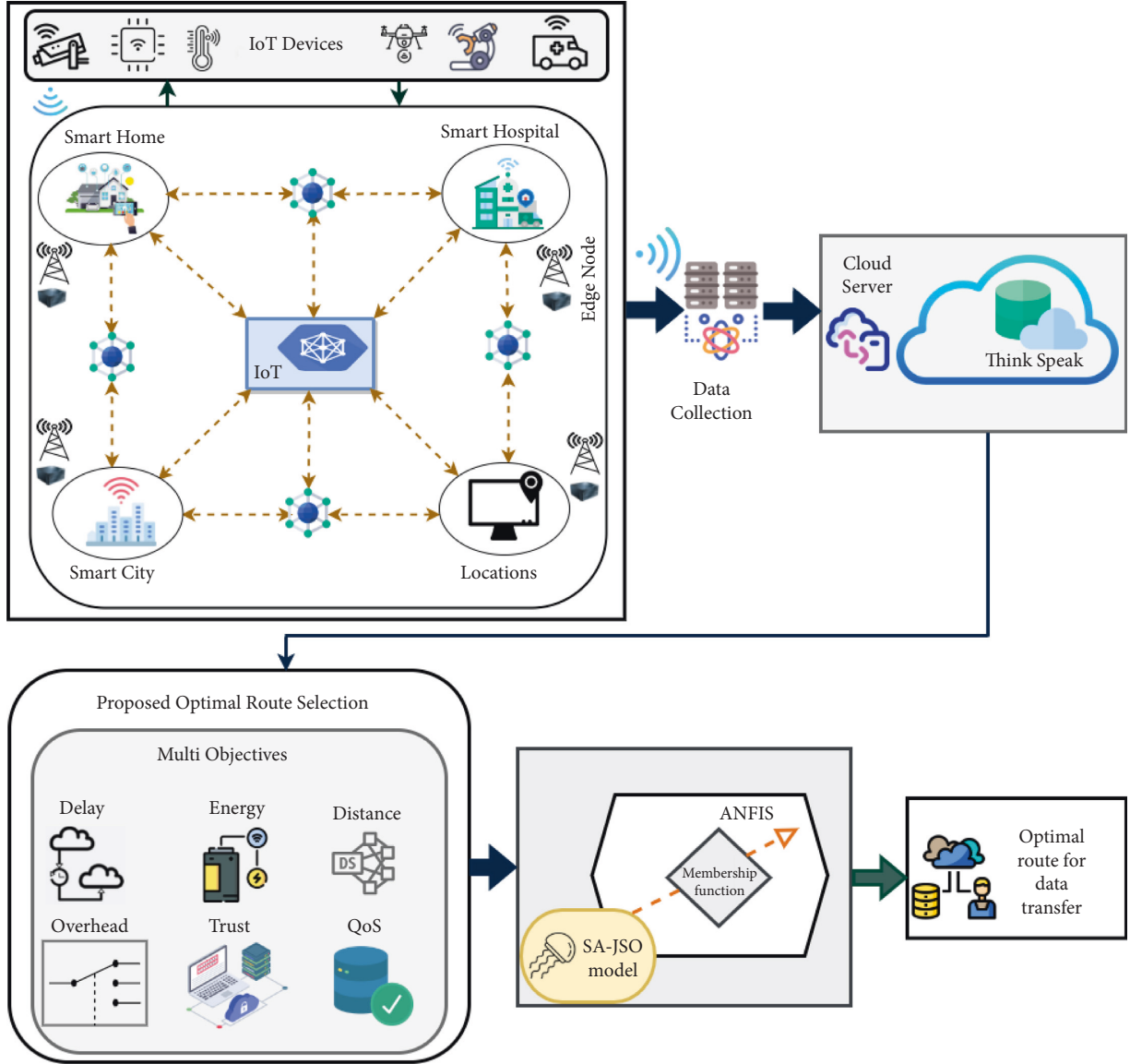


FIGURE 1: Architecture of the proposed routing model.

world can consult or collaborate over the internet. If the patient needs an ambulance in an emergency, the system can transmit the request to the nearest ambulance that is already on its way. Figure 3 shows an illustration of the communication topology of IoT healthcare systems.

5. Description of Multiobjectives

“The main objective of this study is to discover the most optimum route or path for routing the medical data that meet the specific criteria as expressed in equation (1),” wherein f^{energy} , f^{dist} , f^{delay} , f^{head} , f^{trust} , and f^{QoS} refer to fitness function related to energy, distance, delay, overhead, trust (direct and indirect direct), and QoS factor, respectively.

$$\text{Ob} = \min\left(\frac{1}{f^{\text{energy}}} + f^{\text{dist}} + f^{\text{delay}} + f^{\text{head}} + f^{\text{trust}} + f^{\text{QoS}}\right). \quad (1)$$

5.1. Energy. Energy is the vital factor that decides the network life span. The battery cannot be re-energized as there is no source of power. Nevertheless, transmitting data to BS requires extra energy. In equation (2), $E(\rho_l)$ signifies the energy of l^{th} hop, and d_i signifies the count of hops for multihop routing.

$$\text{Energy} = \frac{1}{d_i} \sum_{l=1}^{d_i} E(\rho_l). \quad (2)$$

“The energy consumed during communication $E(P_l)$ is in the form of energy required for transmitting packets E_{TX} , receiving the packet E_{RX} , at idle state E_1 , and energy cost E_{ST} .”

$$f^{\text{energy}} = E_{\text{TX}} + E_{\text{RX}} + E_1 + E_{\text{ST}}. \quad (3)$$

The energy consumed during the packet transmission E_{TX} is mathematically shown as per equation (4).

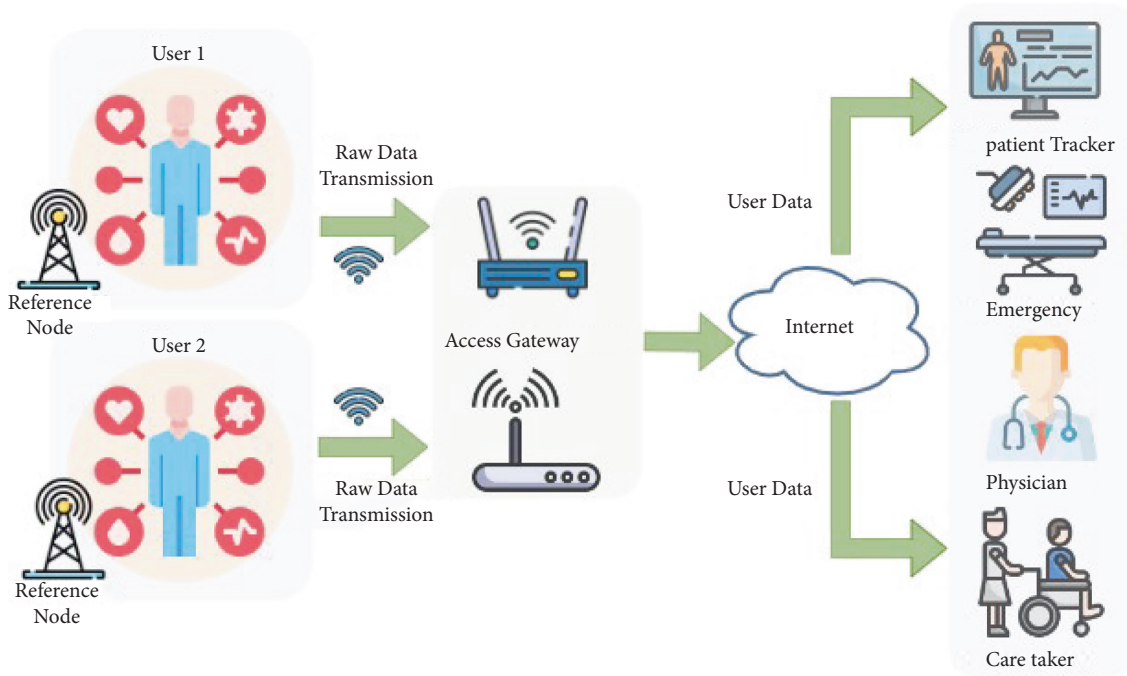


FIGURE 2: Architecture of the IoT healthcare system: an overview.

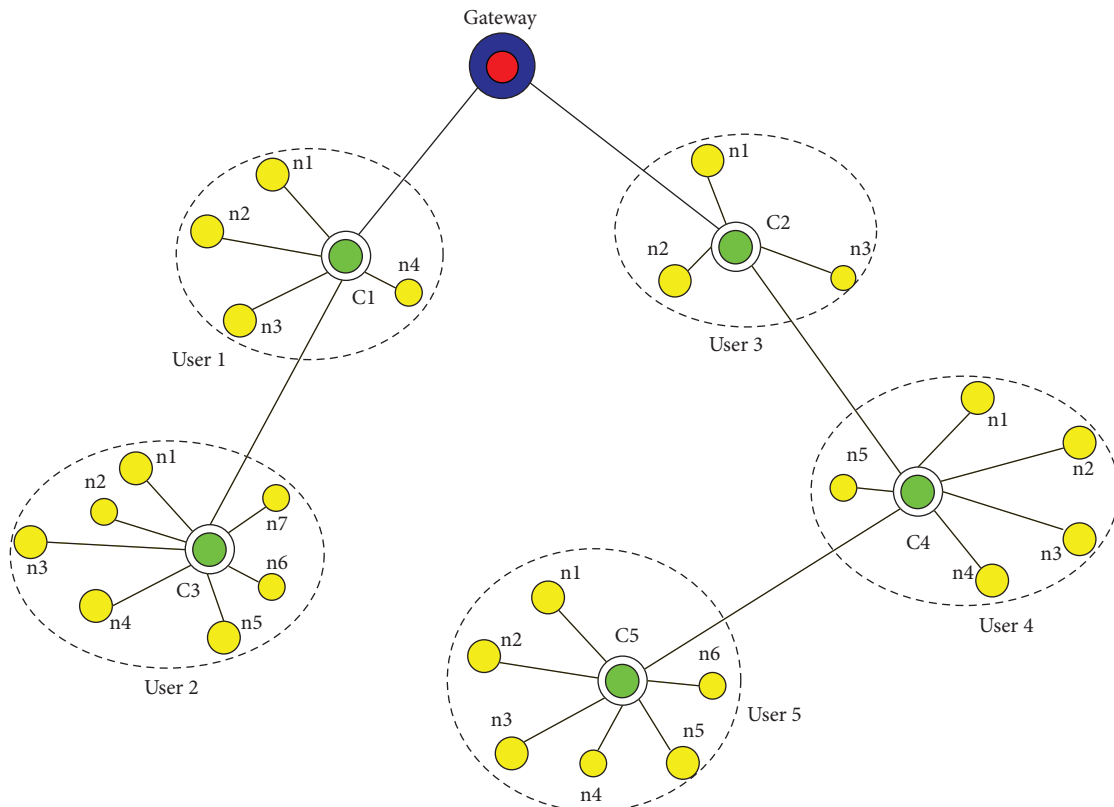


FIGURE 3: The communication topology of IoT healthcare systems: an illustration.

$$E_{TX}(M: e) = \begin{cases} E_{ete} * M + E_{fr} * M * e^2, & \text{if } e < e_0 \\ E_{ete} * M + E_{pr} * M * e^2, & \text{if } e \geq e_0 \end{cases}. \quad (4)$$

Here, $E_{TX}(M: e)$ signifies energy necessary to convey M bytes of packets over e^{th} distance, and E_{ete} signifies electronic energy as described in equation (5). Also, E_{agg} signifies “energy utilization during data collection.” Equation (6) signifies the total energy needed for M packets at distance D_i . Equation (7) signifies the threshold energy e_0 .

$$E_{ete} = E_{TX} + E_{agg}. \quad (5)$$

$$E_{agg} = E_{fr} e^2. \quad (6)$$

$$e_0 = \sqrt{\frac{E_{fr}}{E_{pr}}}. \quad (7)$$

Accordingly, E_{pr} signifies γ “power amplifier energy” and E_{fr} signifies energy essential to employ a free-space system.

5.2. Delay. Delay is a significant QoS constraint for forwarding data. “It is known as the hope ratio necessary for the total number of routing nodes in the network” and is shown in equation (8), wherein d signifies the traveled distance.

$$f^{\text{delay}} = \frac{d}{\text{speed}}. \quad (8)$$

5.3. Distance. The distance (f^{distance}) amid nodes is a vital factor in portraying the network’s lifetime. The fitness for f^{distance} is shown by equation (9), wherein v signifies node’s speed and t signifies time.

$$f^{\text{distance}} = v \times t. \quad (9)$$

5.4. Trust Model. All network hops include a higher trust degree that might be deployed for assessing the trust level among the respective nodes and hops nearby it. There are 2 types of trust model: (i) direct trust and (ii) indirect trust, which are shown in equation (9).

$$f^{\text{trust}} = \{T^D + T^I\}. \quad (10)$$

- (i) Direct trust (T^D): “The direct trust is known as local trust, and it presents the trust value as an agent to determine the familiarities with the target agent.” It is formulated as in equation (12), where $B_{v_1, v_2}(t)$ correctly signifies forwarded packet count by node v_2 to v_1 at time t . In addition, $C_{v_1, v_2}(t)$ signifies packet count transferred by node v_2 from v_1 at time t .

$$T^D(t) = \frac{B_{v_1, v_2}(t)}{C_{v_1, v_2}(t)}. \quad (11)$$

- (ii) Indirect trust (T^I): “It is determined from the knowledge obtained through other hops. The

knowledge of other hops helps in deciding each transaction.” It is formulated as in equation (13), wherein q signifies the nearest node count.

$$T^I(t) = \frac{1}{q} \sum_{n=1}^q T^D(t) \quad (12)$$

5.5. QoS. The QoS is the procedure for managing the network resources to reduce network jitter, latency, and packet loss. The fitness function related to QoS f^{QoS} is mathematically formulated as in equation (14), wherein R signifies node security.

$$f^{\text{QoS}} = \text{mean}(R). \quad (13)$$

5.6. Overhead. In sensor networks, the reception and transmission of packets add overhead, and thus, it is essential for communication. Header length and message monitoring must be reduced, as they could raise connectivity costs. The increasing count of routing packets swapped throughout the simulation is termed as routing overhead. The fitness regarding overhead is signified by f^{overhead} .

6. Optimized ANFIS for Data Routing via SA-JSO Model

6.1. ANFIS Model. In this work, ANFIS is deployed for optimal route selection for routing the medical data. It usually contains five layers that are described as follows.

At the initial (fuzzy) layer, the membership degrees of all linguistic variables are computed. For instance, if only 2 membership functions (MF) are there for every input X and Y , the output of fuzzy layer is attained as in equations (15) and (16), wherein μG_i and μF_i correspondingly signify membership function of X and Y .

$$\mu G_i^1 = \mu G_i(X), \quad i = 1, 2, \dots, n. \quad (14)$$

$$\mu F_i^1 = \mu F_i(Y), \quad i = 1, 2, \dots, n. \quad (15)$$

Second layer: Here, the “AND part in the if-then rules” is employed in the fuzzy system. “If-then fuzzy rules in ANFIS” are described below, wherein n signifies rule count, and p_i , q_i , and ra_i signify constraints, which are illustrated throughout the training phase.

“Rule I: If X is G_i and Y is F_i , then $u_i = p_i X + q_i Y + ra_i$, $i = 1, 2, \dots, n$.”

The output of the second layer is attained as shown in equation (16).

$$U_i^2 = w_i = \mu G_i(X) \times \mu F_i(Y), \quad i = 1, 2, \dots, n. \quad (16)$$

Third layer: At this layer (normalized layer), the weights computed at the prior layer are normalized by equation (17).

$$U_i^3 = \bar{w}_i = \frac{w_i}{\sum_{i=1}^n w_i}, \quad i = 1, 2, \dots, n. \quad (17)$$

Fourth layer: The system output is affected by every node by multiplying its standard weight in “fuzzy if-then rules” as shown in equation (18).

$$U_i^4 = \bar{w}_i u_i = \bar{w}_i (p_i X + q_i Y + r_i), \quad i = 1, 2, \dots, n. \quad (18)$$

Fifth layer: At last, at the 5th layer, every input signal to the layer is combined and this is said to be the output of the system as shown in equation (19).

$$U_i^5 = \sum_{i=1}^n \bar{w}_i u_i, \quad i = 1, 2, \dots, n. \quad (19)$$

In this work, the membership function denoted by μ is fine-tuned using the SA-JSO model.

6.2. Proposed SA-JSO Model. In this work, the membership functions denoted by (μ) are optimally chosen via the SA-JSO scheme. Figure 4 shows the representation for membership functions of ANFIS that are given as input for optimization, wherein wn represents the entire count of membership functions.

Even though the conventional JSO [20] model contains a variety of enhancements, it suffers from specific limitations. Hence, certain modifications are needed and a new algorithm is developed. Generally, self-improvement is established to be capable in conventional optimization schemes. The steps followed in the proposed SA-JSO are as follows.

The JSO encompasses 3 rules: “(1) jellyfish either follow the ocean current or move inside the jellyfish swarm, and a mechanism called “time control” governs the switching between these types of motions. (2) Jellyfish move in the ocean to search for food. They are more attracted to positions where the quantity of available food is greater. (3) The quantity of food found is determined by the location and the objective function.”

Ocean current: It includes numerous nutrients; as a result, the jellyfish are fascinated by it. The orientation of ocean current (Trend) is modeled as shown in equation (20), wherein L^* refers to the location of the present best jellyfish in a swarm; μ refers to the average value of every jellyfish location.

$$\vec{\text{Trend}} = L^* - 3 \times \text{ra}(0, 1) \times \mu. \quad (20)$$

Thus, the updated location of every jellyfish is specified as in equation (21), wherein $L_i(\text{it})$ refers to the location of i^{th} jellyfish at the time it.

$$L_i(\text{it} + 1) = L_i(\text{it}) + \text{ra}(0, 1) \times \vec{\text{Trend}}. \quad (21)$$

Jellyfish swarm: A larger group of jellyfish is known as a swarm, wherein the jellyfish travel about their own positions (passive movement, type P) or a new position (active movement, type S). While the swarm was produced, the

majority of jellyfish reveal P type of motion. Based upon time, they gradually show type S movement. Type P is the movement of jellyfish around their own locations. Conventionally, the updated locality of every jellyfish is computed based upon its position; however, as per the developed SA-JSO model, the location is updated based upon pseudorandom scalar integer ($\text{ra}_i([1, 2])$) as shown in equation (22). In equation (23), $L_{\text{best}}(\text{it})$ refers to the location of jellyfish and $\text{ra}_i([1, 2])$ allows exploring the whole neighborhood of the best jellyfish, it lies among 1 and 2, and lb and ub correspondingly refer to lower and upper bound of searching space.

$$L_i(\text{it} + 1) = L_{\text{best}}(\text{it}) + (-1)^{\text{ra}_i([1, 2])} \times \text{ra}(0, 1) \times (\text{ub} - \text{lb}). \quad (22)$$

In addition, the proposed SA-JSO model includes an adaptive convergence strategy as modeled in equation (23).

$$L_i(\text{it} + 1) = L_{\text{best}}(\text{it}) + \text{rand}^* \left(\vec{L}_{\text{rand}1}(\text{it}) - \vec{L}_{\text{rand}2}(\text{it}) \right) + (1 - \text{rand})^* \left(L^* - \vec{L}_{\text{rand}3}(\text{it}) \right). \quad (23)$$

In equation (23), rand 1, rand 2, and rand 3 refer to the indices of 3 solutions randomly picked from the populations and rand refers to control constraint that lies among 0 and 1.

Moreover, the time control mechanism is introduced for regulating the movement of jellyfish that deploys threshold constant c_{th} and time control function $c(\text{it})$. Here, $c(\text{it})$ is computed as in equation (24), where it_{max} signifies maximal iteration. Algorithm 1 explains implemented SA-JSO model.

$$c(\text{it}) = \left| \left(1 - \frac{\text{it}}{\text{it}_{\text{max}}} \right) \times (2 \times \text{ra}(0, 1) - 1) \right|. \quad (24)$$

7. Application

The principal areas of IoT applications are healthcare, the environment, smart cities, and commercial, industrial, and infrastructural fields. IoT can be defined as generating daily information from an object and transferring it to another one. Consequently, enabling communication between objects makes the range of IoT applications extensive, variable, and unlimited. Hence, the developed ANFIS + SA-JSO model can be used to find the location of nodes in prior and forward the data packets toward the destination. At the same time, the developed method can also be used in different applications with different cases as shown in Table 3.

In healthcare programs, objects collect information about patients and send it to remote nursing stations using communication networks, especially the internet. Analysis of information in nursing stations can lead to timely treatment for patients and can also prevent potential risks for patients. Given that some patients may be in critical condition, the rapid and reliable transfer of data to the nursing station can avoid death. Patient data transfer from a remote point to a clinic or hospital, integration of medical devices, and the possibility of data exchange between them improve medical experiments in providing care. It also

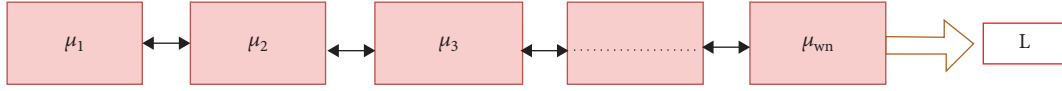
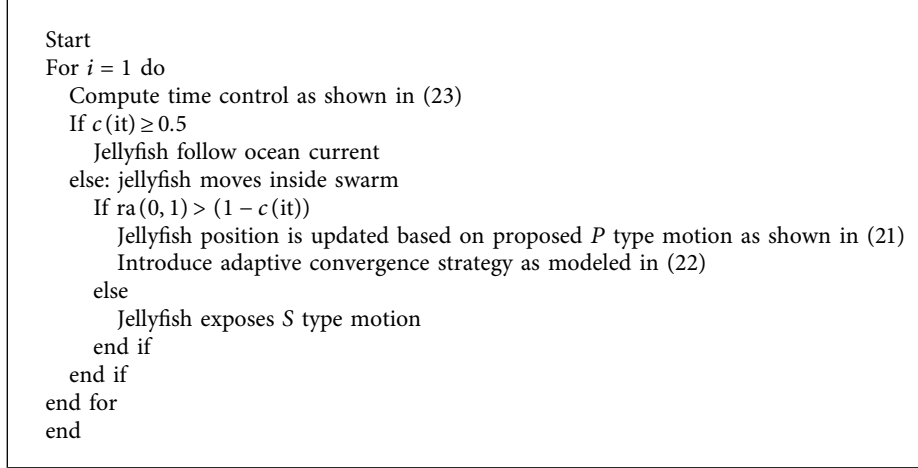


FIGURE 4: Solution encoding.



ALGORITHM 1: Implemented SA-JSO model.

promotes interaction between physicians about the effect of the drug, management and controlling various connecting devices, the possibility of medically transmitting IoT information by physicians, accurate diagnosis of other health problems and control patterns (heart rate, temperature, blood pressure, and blood sugar levels in the body and gastrointestinal tract), the possibility of transmission, and the information used by the physician to process and perform the appropriate medical activity.

8. Results and Discussion

8.1. Simulation Procedure. The suggested EER protocol in the IoT healthcare data routing model was implemented in MATLAB. The data that support the findings of this study are openly available in the UCI repository at <https://archive.ics.uci.edu/ml/datasets/heart+disease> [21] reference number. “There are 76 attributes in this database, but all published studies only use a subset of 14 of them. The Cleveland database, in particular, is the only one that has been used by machine learning researchers yet. The ‘goal’ field indicates whether or not the patient has cardiac disease. It has an integer value ranging from 0 (no presence) to 4. Experiments with the Cleveland database have concentrated on simply attempting to distinguish presence (values 1, 2, 3, and 4) from absence (value 0).” The analysis was performed for two groups: group 1 (long-distance data transfer, i.e., end-to-end) and group 2 (short-distance data transfer (40% of distance), and the simulation parameters considered for the developed scheme are shown in Table 4. Every evaluation is performed by correspondingly setting the node counts at 100, 250, 750, and 1,000. Accordingly, an assessment of the proposed scheme was performed over the existing models such as ANFIS + MFO, [22] ANFIS + SLnO [23] ANFIS + DA

[24], ANFIS + JSO, and Fuzzy + HHO, [25] regarding “convergence analysis, fitness, life span, PDR, residual energy, and statistical evaluation.”

The IoT-WSN for routing the medical data is simulated in an area of 100 m × 100 m, and the node speed is predetermined as 2 m/sec. The network is modeled in form of a “graph $G(V, E)$, with N counts of nodes denoted as $V = \{v_1, v_2, \dots, v_n\}$ and m counts of edges $E = \{e_1, e_2, \dots, e_m\}$.” The network is considered as a homogeneous one, wherein every node carries equivalent sensing area and processing power as well. During node deployment, every node is assumed to include a similar energy level. When a node is employed, they are regarded as static and then every node in the communiqué range transmits a HELLO message together with the node ID. The symmetric form of communiqué occurs amid the SNs while they are in the communiqué range R . The communiqué may be asymmetric or symmetric. For symmetric communiqué, the node v_1 arrives v_2 , and v_2 arrives v_1 as well. If the distance between v_1 and v_2 is lesser than R , then they both directly converse with one another. If distance between v_1 and v_2 is superior to R , nevertheless, there are no ways for them to directly commune. The only cause following the drain of the node is its energy exhaustion.

8.2. Statistical Analysis. The statistical analysis of the implemented ANFIS + SA-JSO model over other traditional models for varied metrics is shown in Tables 5 and 6 for 2 groups. “As meta-heuristic schemes are stochastic in nature, every algorithm is executed for the number of times to attain the statistic of the objective function.” The adopted ANFIS + SA-JSO model demonstrates the superior outcomes when evaluated over conventional schemes such as

TABLE 3: IoT healthcare applications.

Focus area	Applications	Device
Disease management system	IoT healthcare service providers	Independent handheld devices and smartphones
Synthesis method for e-health to ensure high availability	New structure for e-health	In connection with the patient's body

ANFIS + MFO, ANFIS + SLnO, ANFIS + DA, Fuzzy + HHO, and ANFIS + JSO models. From Table 5, the proposed ANFIS + SA-JSO model under the median case scenario attained superior values over certain distinguished schemes. In certain scenarios, the conventional schemes have exhibited better values; however, the cost function of the developed model has accomplished optimal values, and therefore, this variation can be considered negligible. Likewise, better results have been obtained by the proposed work for group 2 in specific scenarios. Thus, the improvement of the proposed NIS + SA-JSO model over the other conventional methods is proved.

8.3. Convergence Analysis. Figures 5 and 6 describe the analysis of the adopted ANFIS + SA-JSO scheme over traditional schemes such as MFO, SLnO, DA, and JSO for group 1 and group 2 scenarios. Here, analysis is performed by fixing the node counts for 4 variations such as 100, 250, 750, and 1,000, respectively. The evaluation is performed by adjusting the iterations from 0, 5, 10, 15, 20, 25, and 30 to 35, respectively. The resultants attained for group 1 by fixing node counts at 100, 250, 750, and 1,000 are shown in Figure 6. On observing the analysis outcomes, the proposed ANFIS + SA-JSO model has attained minimal values for all node counts when compared to the existing schemes. Initially, from iteration 0 to iteration 5, the cost values are found to be higher for proposed and evaluated models; however, as the iteration count increases, better outputs are attained. That is, from iteration 5 to 30, the cost values go on reducing for proposed and compared models; nevertheless, the adopted ANFIS + SA-JSO scheme exhibits least values when compared to the existing ones for both group 1 and group 2. Moreover, it can be noticed that subsequent to the proposed approach, the JSO approach has attained better outcomes than MFO, SLnO, and DA models for both group 1 and group 2. Predominantly, the adopted scheme is converged better for node count of 1,000 for group 1, i.e., the presented approach has accomplished a least-cost value (almost 0.01) since it is enhanced via the ANFIS + SA-JSO optimization theory. Thus, the overall evaluation shows the enhancement of the presented model with the optimization-assisted ANFIS technique. The optimized membership function of ANFIS has thus ensured better efficacy to attain optimal geographic routing for routing the medical data depending upon the defined multiobjectives.

8.4. Analysis of Network Life Span. The life span of the network is said to be a major aspect of WSN that is directly accountable for increasing the network's endurance. The lifetime extension of the network is the most important

TABLE 4: Simulation parameters.

Channel type	Wireless
Antenna	Omni antenna
Dimension X	100 m
Dimension Y	100 m
Total simulation time	10 s
Number of nodes	50, 100, 150, 200

confront of the WSN. The majority of the existing works have established novel schemes to prevail over this confront; however, they did not offer much satisfactory outputs. Thereby, this work focused on achieving the best routing network with lower energy utilization, and this is clear from the obtained outcomes as exposed in Figure 7. In considering group 1, the network life span is highly amplified for all variations in the node count. Particularly, at node variations of 500 and 800, the suggested model has attained a higher life span of the network (around 3), whereas at node variations of 100 and 1,000, the suggested model has attained a network life span with the value of 2 for group 1. At node count = 200, the life span of the ANFIS + SA-JSO is much better than ANFIS + MFO, ANFIS + SLnO, ANFIS + DA, and ANFIS + JSO, respectively. Therefore, the ANFIS + SA-JSO model is definitely the first rate for EEG routing, since it has achieved the chief goal of lifetime growth.

8.5. Analysis of Fitness. The resultants acquired regarding fitness for group 1 and group 2 scenarios are revealed in Figure 8. As per equation (1), the fitness (considering energy, distance, delay, overhead, and trust (direct and indirect direct and QoS factor)) of the developed model should be minimal, thereby ensuring better data transmission. Here, on noticing the resultants, the developed ANFIS + SA-JSO has accomplished minimal fitness for all node variations for both group 1 and group 2 scenarios. On examining the resultants from group 1, when the count of nodes = 100, the ANFIS + SA-JSO has accomplished the optimal fitness value around 0, whereas, at other node variations, the ANFIS + SA-JSO model has accomplished relatively higher values of 10, 10, and 10 in that order.

Likewise, on observing the resultants from group 2, when the count of nodes = 100, the ANFIS + SA-JSO has acquired the optimal fitness value around 0, while, at other node variations, the ANFIS + SA-JSO model has acquired comparatively higher values of 10, 10, and 15 in that order. Also, for group 2, the developed model has achieved the least value of 15 at node variation of 200, whereas the existing models such as ANFIS + SLnO, ANFIS + DA, ANFIS + JSO, and ANFIS + MFO, and Fuzzy + HHO have acquired relatively higher values of 700, 700, 700, 100, and 50 in that

TABLE 5: Statistical analysis for adopted model over existing models for group 1 scenario.

Measures	ANFIS + SLnO	ANFIS + DA	ANFIS + JS	ANFIS + MFO	Fuzzy + HHO [38]	ANFIS + SA-JSO
Median	11.028	44.033	11.028	5.2934	25.672	5.2934
Worst	1988.4	2295.5	440.46	1049.9	94.783	61.553
Best	546.34	728.29	146.71	286.01	53.193	36.609
Mean	92.949	286.78	67.669	44.414	46.159	39.795
Std	963.32	1058.5	198.59	509.61	29.792	23.517

TABLE 6: Statistical analysis for adopted model over existing models for group 2 scenario.

Measures	ANFIS + SLnO	ANFIS + DA	ANFIS + JS	ANFIS + MFO	Fuzzy + HHO [38]	ANFIS + SA-JSO
Worst	3.368	77.616	3.368	3.368	20.32	3.368
Best	1882.8	1887.3	1887.3	3578.1	96.458	102.58
Median	498.51	657.48	594.06	922.35	42.099	53.468
Mean	53.965	332.49	242.76	53.965	25.809	53.965
Std	923.5	828.85	871.87	1770.9	36.378	48.128

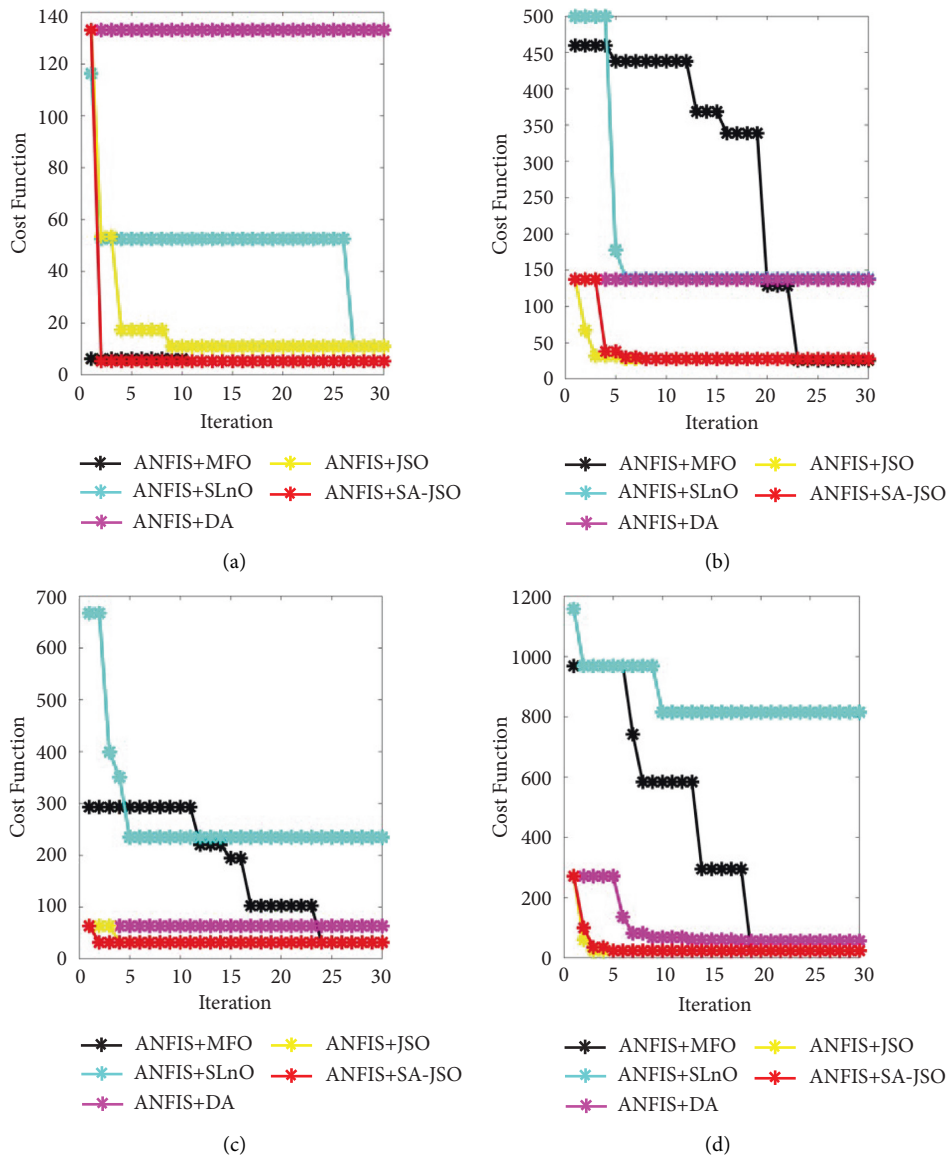


FIGURE 5: Convergence analysis of developed approach over compared approaches regarding group 1 scenario by fixing counts of nodes as (a) 100, (b) 250 (c) 750, and (d) 1,000.

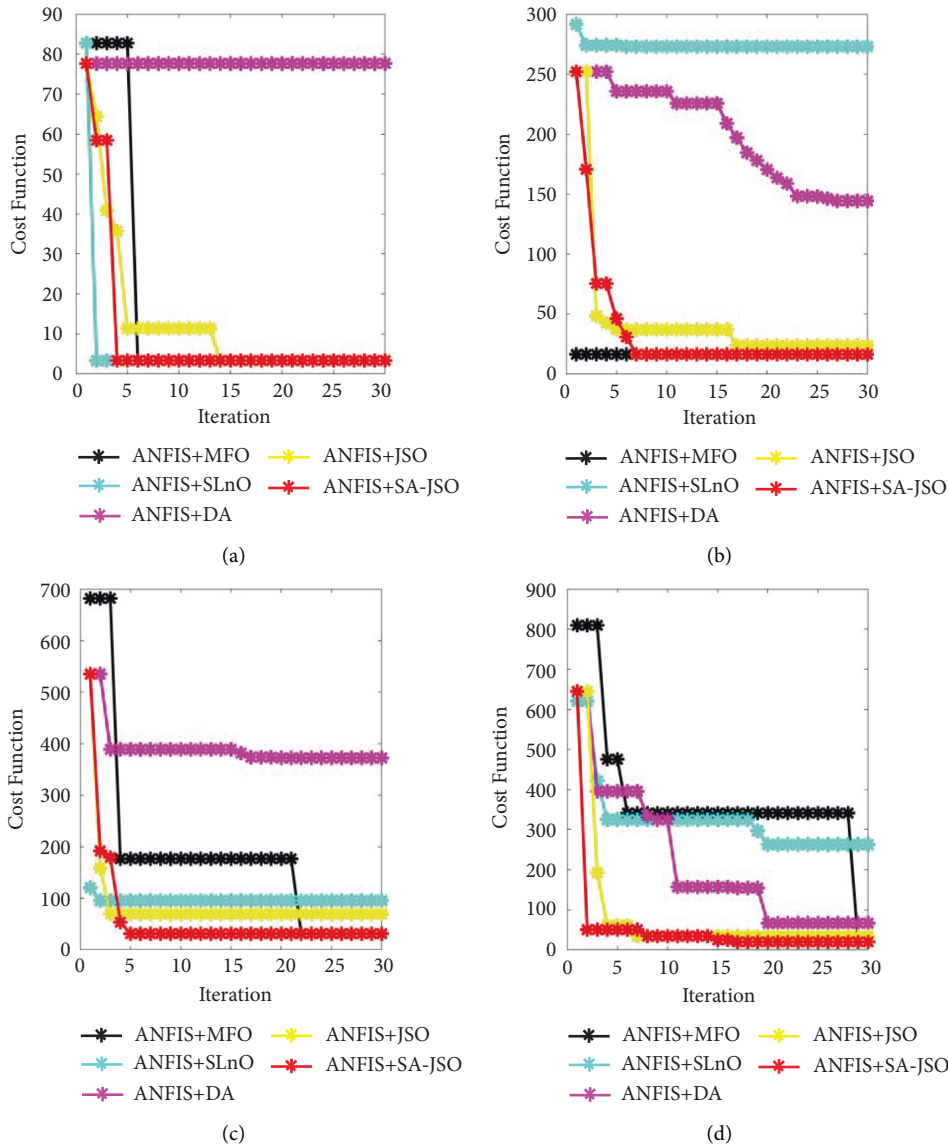


FIGURE 6: Convergence analysis of developed approach over compared approaches regarding group 2 scenario by fixing counts of nodes as (a) 100, (b) 250 (c) 750, and (d) 1,000.

order. Thus, the improvement of the developed model regarding fitness was established from the results.

8.6. *Residual Energy.* The remaining energy left after transmitting and receiving medical data is known as residual energy. The network with high residual energy has the maximum network life span, and as a result, the reliability will be higher for data transmission. Figure 9 shows the resultants acquired for group 1 and group 2 scenarios regarding residual energy. Here, analysis is performed for varied node variations such as 100, 250, 750, and 1,000. For

both group 1 and group 2 scenarios, the residual energy is found to be higher for all node variations. Moreover, the Fuzzy + HHO has acquired the nearby values as that of the developed ANFIS + SA-JSO scheme for both scenarios; however, the developed approach has acquired much superior values than the Fuzzy + HHO scheme, thus proving the supremacy of the adopted optimization-assisted ANFIS model. In particular, for the group 2 scenario, the developed approach at node count of 200 has exhibited a higher value of 98, which is better than the existing ones. Hence, from the overall assessment, it is apparent that the ANFIS + SA-JSO model had achieved the top residual energy.

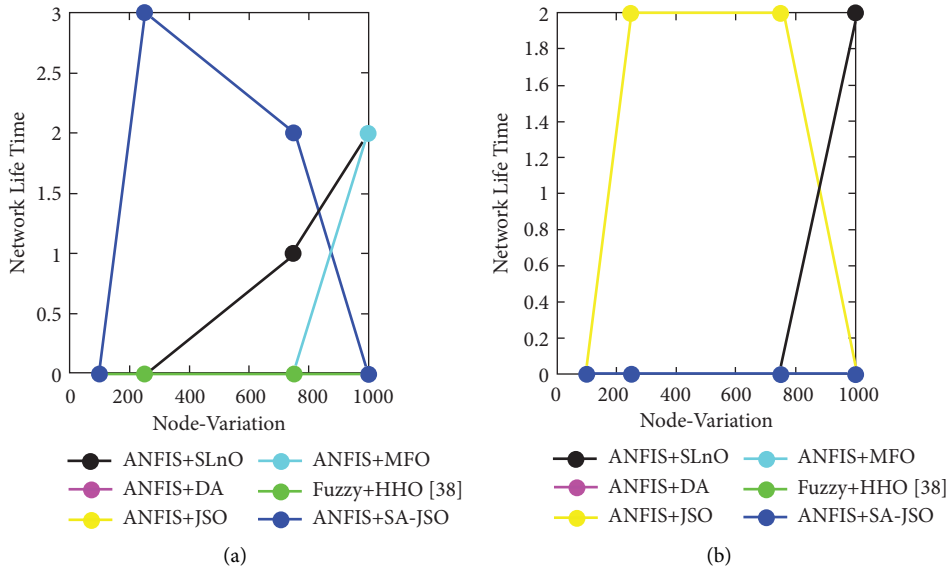


FIGURE 7: Analysis of the life span of developed approach over compared approaches regarding (a) group 1 and (b) group 2.

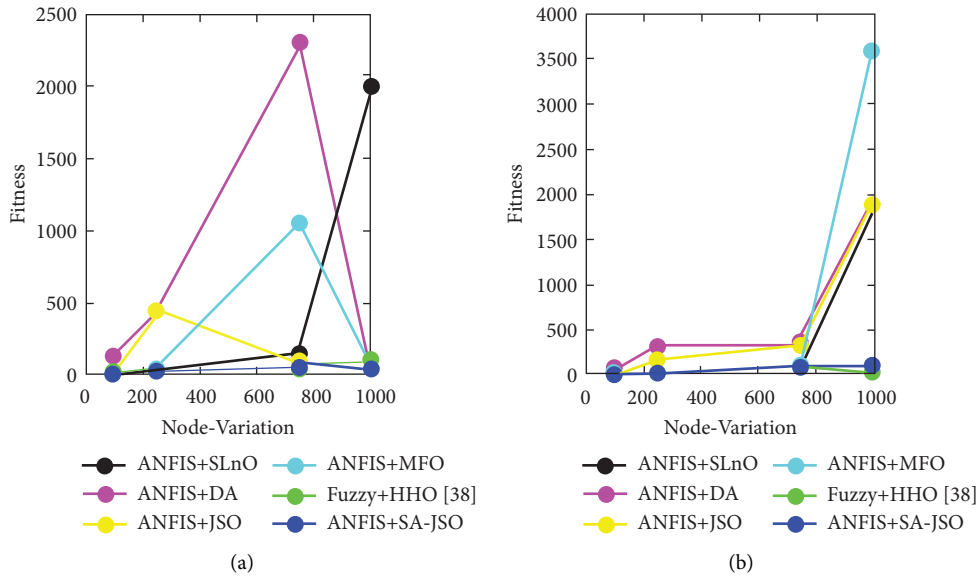


FIGURE 8: Analysis of PDR for developed approach over compared approaches regarding (a) group 1 and (b) group 2.

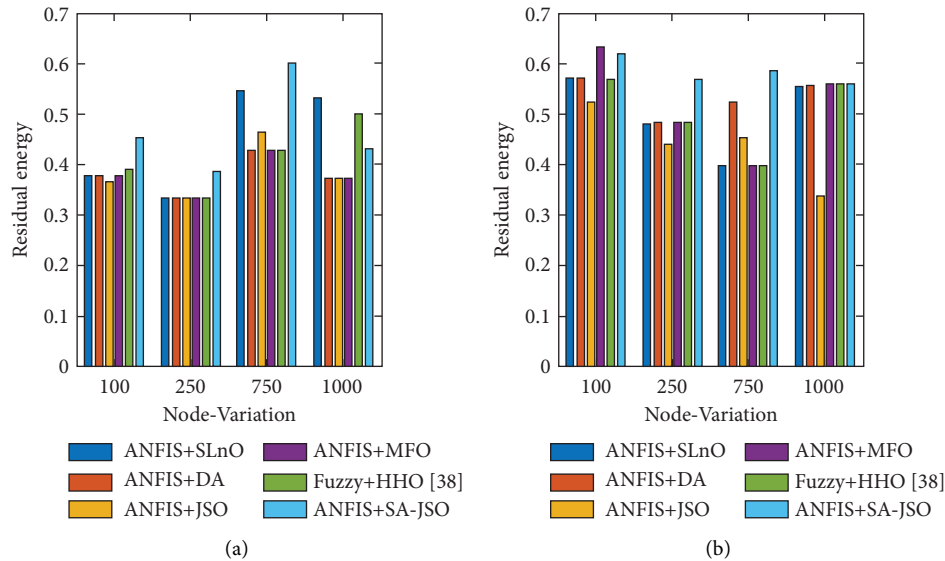


FIGURE 9: Analysis of residual energy for developed approach over compared approaches regarding (a) group 1 and (b) group.

9. Conclusions

A novel medical data routing protocol was developed in this research work depending upon the defined multiobjective functions. Throughout the routing, the most optimal routes were chosen by optimized ANFIS, in which the membership functions were optimized. The optimal route selection considered energy, distance, delay, overhead, QoS, and trust. Here, the ANFIS + SA-JSO model was deployed for optimization. On observing the analysis outcomes, the proposed ANFIS + SA-JSO model has attained minimal values for all node counts when compared to the existing schemes. Initially, from iteration 0 to iteration 5, the cost values were found to be higher for proposed and evaluated models; however, as the iteration count increased, better outputs were attained. That is, from iteration 5 to 30, the cost values go on reducing for proposed and compared models; nevertheless, the adopted ANFIS + SA-JSO scheme exhibited least values when compared to the existing ones for both group 1 and group 2. Also, for both group 1 and group 2 scenarios, the residual energy was found to be higher for all node variations. Moreover, the Fuzzy + HHO has acquired the nearby values as that of the developed ANFIS + SA-JSO scheme for both scenarios; however, the developed approach has acquired much superior values than the Fuzzy + HHO scheme, thus proving the supremacy of the adopted optimization-assisted ANFIS model. As a result, the adopted routing model for medical data transmission was recommended as a suitable one. In the future, this work may take into account the time parameter, and it would also be fascinating to apply our strategy to networks with heterogeneous propagation properties.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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