

Research Article

Presenting a Reliable Routing Approach in IoT Healthcare Using the Multiobjective-Based Multiagent Approach

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Received 28 January 2021; Revised 28 July 2021; Accepted 31 August 2021; Published 29 September 2021

Academic Editor: Ihsan Ali

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Developments in information and related technologies have led to a wider use of the Internet of things (IoT). By integrating both virtual and physical worlds, IoT creates an integrated communication framework of interrelated things and operating systems. With the advent of IoT systems based on digital remote care, transferring medical data is becoming a daily routine. Healthcare is one of the most popular IoT applications and tries to monitor patients' vital signs during the day for weeks and to eliminate the need for hospitalization. In a healthcare system, many sensors are installed to collect the patient's information, including environmental monitoring sensors and vital and unstructured message sensors in order to reduce the patients' expenses. The IoT network contains flexible sensors in dynamically changing environments where sensors collect environmental information and send it to nursing stations for healthcare applications. Due to the wireless nature of IoT networks, secure data transmission in the healthcare context is very important. Data collected from sensors embedded in healthcare devices may be lost for various reasons along the transmission path. Therefore, establishing a secure communication path in IoT networks in the context of healthcare is of great importance. In this paper, in order to provide a reliable data transfer protocol in the context of healthcare, a reliable routing using multiobjective genetic algorithm (RRMOGA) method is presented. The contribution of this paper can be summarized in two steps: (i) using a multiobjective optimization approach to find near-optimal paths and (ii) using reliable agents in the network to find backup paths. The simulation outcomes reveal that the proposed approach, based on the use of the multiobjective optimization approach, tries to find optimal paths for information transfer that improve the main parameters of the network. Also, the use of secure agents leads to a secure information transfer in the network in the context of healthcare. Experimental results show that the proposed method has achieved reliability and data delivery rates, 99% and 99.9%, respectively. The proposed method has improved network lifetime, delivery rate, and delay by 14%, 2%, and 5.6%, respectively.

1. Introduction

Recently, the advent of the Internet of things (IoT) has led to a paradigm effect on all regions of human-machine relations [1]. This novel technology has gained popularity in industries, healthcare systems, user interface development, and other areas [2]. IoT is the interconnection of devices, applications, sensors, and network connections that enhances these entities for data collection and data exchange. By integrating the physical and virtual worlds, IoT provides an integrated communication framework for interrelated devices and operating systems [3, 4].

Since IoT networks provide a lot of benefits for monitoring of patients in hospitals and healthcare centers, IoT healthcare applications have received more attention [5]. In the context of healthcare, IoT is one of the most fundamental aspects of the IoT application because it helps healthcare applications make full use of the IoT and cloud resources. The cloud environment provides standard protocols to support the connection between medical equipment and computational resource and transmission of medical data from embedded sensors on smart devices to a network of fog computing [6]. With the advent of IoT systems based on digital healthcare, medical data transmission is becoming

a common task. Therefore, developing an efficient method to support a reliable and secure routing and aggregation of patient biomedical data from the Internet of things is an essential challenge [7]. 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 [8]. Given that some patients may be in critical condition, the rapid and reliable transfer of data to the nursing station can be one of the main challenges in IoT-based healthcare systems [9, 10].

On the other hand, system failure can be another reason for the lack of transfer of data to nursing stations in IoT healthcare programs [11]. System failures may be due to hardware crashes, defective software performance, power leakage, or environmental hazards. In addition, as the number of nodes in an IoT system in healthcare applications increases, the likelihood of errors can also increase and disrupt system performance. Data loss due to system failure in care settings can have a negative effect on the use of healthcare programs and eventually can cause irreparable injuries in patients' bodies [12–14].

In this paper, in order to provide a reliable data transfer protocol in the context of healthcare, a reliable routing using multiobjective genetic algorithm (RRMOGA) method is presented. RRMOGA uses a combination of the multiobjective genetic algorithm to find the optimal paths between nodes in the IoT network and nursing stations and select reliable factors based on the weight of each path in the network to find support paths. Backup routes are introduced to transfer data in case of failure and failure to receive the original data from the optimal route. In the multiobjective genetic algorithm, in the proposed method, a multicriteria objective function is used to improve the main objectives in the network. The criteria related to the evaluation function in the proposed method include the distance between objects, the distance from the node to the destination, the quality of the link, and the degree of reliability. In fact, the node with the lowest hop count to the source node and the shortest straight distance to the access point, with the highest link quality and highest degree of reliability is selected as the optimal and most reliable node in each hop in the network. Also, the backup node is selected as the second optimal node in neighboring nodes with the values of evaluation criteria in the second category, as a reliable factor in the backup path. The selection of optimal nodes at each step leads to global optimization of reliable routing in healthcare systems on the IoT platform. The application of multiobjective genetic optimization algorithms has been proven in many fields of research, including the energy-efficient routing in wireless sensor networks [15], resource allocation in the cloud-fog-IoT infrastructure [16], service placement, and load distribution in edge computing [17]. In general, the contribution of this paper can be summarized in four steps:

- (i) Simulating IoT networks according to standard parameters to extract used data in the proposed method

- (ii) Using a multiobjective genetic algorithm optimization approach to find optimal paths
- (iii) Using reliable agents in the network to find support paths
- (iv) Evaluating the proposed method through known criteria and comparing it with the-of-are methods

In the proposed method, each device as a factor receives a certain amount of reliability based on the number of packets received and the number of packets sent. Getting dynamic network reliability is considered as one of the innovations of this paper. Also, at each step of transferring information from each node to find the next hop, a multiobjective genetic algorithm evaluates the distance between nodes relative to each other, the next hop distance to the destination, the delay between nodes, the quality of links between nodes, and the degree of the reliability value of the nodes in the next hop through fitness function. The use of the multiobjective evaluation function in a genetic algorithm is another innovation in this paper that combines the parameters of quality of service and reliability value. Finally, in order to send packets from the source node, based on the values of the evaluation function, the main path and an alternative path between the source node and the next hop are created. Then, the routing process in the main and alternative route is done using the multiobjective evaluation function. In the end, the two routes are returned as the main and the alternative route. The use of two paths that is the most optimal path in terms of evaluation function values as the main path and the other one as an alternative path has been proposed as another innovation in the proposed method in this paper. The rest of the paper is organized as follows:

In Section 2, the related work will be reviewed. Section 3 will describe the proposed method. Section 4 will provide simulations and evaluation of results. Section 5 concludes and discusses the article results.

2. Background

Patient-centered care services (PCCs) are an emerging healthcare model focused on patients' individual medical needs, originally developed by the Picker/Commonwealth program created by the Picker Institute in 1988. In fact, the node with the lowest hop count to the source node and the shortest straight distance to the access point, with the highest link quality and highest degree of reliability is selected as the optimal and most reliable node in each hop in the network.. They have the necessary training and support to make decisions and participate in self-care. While many initiatives have provided evidence of PCC success on a smaller scale, due to its conflict with the existing hospital-based model, the potential of PCC on a larger scale has not yet been realized in order to eliminate the need for hospitals or clinics. Conversely, the PCC uses these institutions in a common model of patient care using the Internet of things. The Internet of things is the convergence of telecommunications, sensors, actuators, cloud computing, and big data over the Internet to provide specific services [18].

The Internet of things can be customized to meet the challenges of modern healthcare. The healthcare system can be classified into three main areas: (a) large healthcare institutions (e.g., hospitals), (b) small clinics and pharmacies, and (c) nonclinical environments (e.g., homes care, communities, and rural areas without healthcare). To understand the role of the Internet of things in healthcare, firstly, the function of each region must be understood. Because the Internet of things has the ability to perform specific operations at a lower cost and more reliably, higher or more timely, it ultimately affects operations in other areas, resulting in a more stable and self-sustaining healthcare ecosystem [19].

Prior studies in the field of healthcare in the IoT indicate the importance of using applications and the use of the IoT in the field of health since it has an important role in promoting and developing health services and benefits [20–25]. The structure of the Internet of things and the healthcare monitoring systems are described in this section. An IoT-based healthcare monitoring system includes the four main elements of IoT medical equipment, information, and communication technology in the healthcare monitoring system, Internet services, and medical data management and processing [26, 27].

IoT applications in healthcare control systems refer to the use of information and digital communication technology, such as computers and mobile devices, for health management. An Internet application of objects in a healthcare system is also called an electronic health system or mobile healthcare monitoring system (MHCMS) and includes various health services [28].

IoT applications in medical fields such as intelligent sensor control, patient data transfer from a remote point to a clinic or hospital, integration of medical devices, and the possibility of data exchange between them, improves medical experiments in providing care. It also promotes interaction between physicians about the effect of the drug, management and controlling various connecting devices, the possibility of transmitting IoT information medically by physicians, accurate diagnosis of other health problems and control patterns (heart rate, temperature, blood pressure, 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. Devices connected to you are vital throughout the day, transmitting wirelessly to medical devices such as computers and smartphones. Overall, there is a tremendous potential for Internet-connected healthcare control systems and smart medical equipment for the well-being of the people. IoT healthcare systems have been used in various cases such as reducing preparation time for work in emergency rooms [29], personal health records [30], remote monitoring of patient health [31], and communicate specialists [32].

2.1. Related Works. Due to the widespread use of healthcare and monitoring applications in the context of IoT networks, the importance of secure data transmission in the network has been increasingly considered. Therefore, many

researchers have tried to provide a reliable routing protocol in IoT networks for healthcare applications, which we will mention in the article.

Woo et al. have developed a secure oneM2M-based IoT network for individual hygiene equipment. In order to have a dedicated application sensor, in this paper, the protocol between ISO/IEEE 11073 protocol messages has converted to oneM2M messages at the access point embedded in the devices and the management server. The oneM2M-based IoT system is built for personal hygiene devices and has been evaluated in various experiments [11]. The result of experiments has shown that the oneM2M-based IoT system transmits secure messages but the disadvantage of this method is the lack of attention to other factors of service quality. Critical messages may be transmitted over the network that needs to be sent immediately, but such situations have not been considered in the oneM2M-based IoT system.

Soufiene et al. have categorized healthcare information in the IoT into two categories: priority emergency and crucial health signals. Emergency signals have the highest priority among signals and should be sent securely as soon as possible. Crucial health signals are data that physicians request to continue monitoring patients. This paper uses direct transmission to forward important data using multi-step communication to deliver crucial health information [33]. The main idea of this method is the rapid transmission of critical data in the IoT network, while the loss of these critical messages can cause great damage. The main disadvantage of this method is that it does not consider the amount of reliability to the devices in the multistep path specified in the network to send critical data.

The Sarwesh et al. node location placement method and reliable routing mechanism in the environment of the IoT network have been extended. In this method, sensor nodes and relay nodes have been utilized. Sensor nodes have been defined as responsible for gathering signals, and relay nodes have been defined as responsible for data combination and path reliability control. In the node placement method, the density of the intermediate nodes varies due to the traffic region, to avoid the problem of energy holes. In the routing method, to decrease the number of retransmissions, the route is calculated efficiently and reliably [34]. The main disadvantage of this method is that it does not use a backup path to send packets. If something happens on the main route and the data is not sent, the delay in sending the message to resend the data will be very high.

Gochhayat et al. have proposed a new distributed key administration structure for the IoT platform. The method presented in this paper resourcefully provides IoT systems by assigning more cryptographic processing resources to local agents. These agents are coordinated with other peers to create a distributed key as well as an authentication mechanism for network things. Specifically, the presented method utilizes the benefits of mobile agents and deploys them in diverse subnets if necessary for the authentication process [35]. The disadvantage of this method is the lack of reliability evaluation for the distributed key controller agents.

Conti et al. have developed the REMI method, a trustworthy multihop routing method for IoT networks. The core

purpose of this article is to facilitate effective transmission in power efficiency networks like the Internet of things, ensuring that messages are received from arbitrary source nodes, regardless of network dimensions and the existence of defective nodes. REMI uses a multistep clustering method that speeds up the transmission of messages across the network [36]. The disadvantage of this method is energy-based routing in the IoT network, while other parameters of service quality and, most importantly, reliability do not play a role in the next hop selection.

Lyu and Yi conducted an in-depth study on IoT communication and network trustworthiness in a complex framework. In this article, an artificial bee colony optimization algorithm has been used to obtain the near optimal path from each node to the nearest head cluster. The implementation of this method in the IoT framework shows that the presented method can efficiently decrease the amount of data forwarded to the base station by sensor nodes through cluster head union. Data collection efficiency, energy balance, and reliability as well as network lifetime are also improved. [37]. The disadvantage of this method is the use of a single objective fitness function based on reliability in the bee colony optimization algorithm, and other service quality parameters are not considered as the goals of the fitness function.

In 2019, Asghari et al. presented a medical monitoring plan for the cloud-based IoT platform in which patients' medical conditions are predicted by extracting their physiological data collected from IoT devices, and then, other medical results are obtained. The disease diagnosis model is used to analyze patients' medical data to provide a hygienic/medical prescription. After the results are confirmed by the medical team, it is sent to the patient. The patient then identifies their nonsurgical needs such as location, cost, and time to find the most appropriate combination of health/medical services based on their preferences. Experimental results show that the proposed scheme for achieving effective disease diagnosis for combined health/medical prescriptions is successful [38]. This method greedily tries to send data to patients in need of surgery, while greedy selection may lead to local optimization and routing may not be as efficient.

In 2020, Asghari et al. proposed a privacy-aware cloud service combination approach to optimize service quality in the IoT environment by providing a hybrid IoT-based cloud service concept model on the privacy level calculation model and an algorithm. They have proposed a new hybrid evolution using the shuffled frog leaping algorithm (SFLA) genetic algorithm (GA), known as SFLA-GA. The proposed algorithm is used to optimize the composition of the proposed services in terms of the accumulation of different quality factors as the value of appropriateness. Also, to help users choose the right combination service, they are categorized in terms of the level of privacy that is achieved through a computational model. The simulation results showed that the proposed method improves the fitness compared to other contemporary algorithms [39]. Using an optimal path and not considering the backup path for emergencies can be considered a disadvantage of this method.

In 2020, Asghari et al. critical data is collected through IoT monitoring objects, and then, data analysis has been

done through various machine learning methods such as the decision tree (J48), sequential minimum optimization (SMO), multilayer perceptron (MLP), and Naïve Bayesian (NB). Classification is required to identify the level of potential risks of physiological and behavioral changes in the elderly. Experimental results confirm that the SMO, MLP, and NB classifiers perform almost closely in terms of accuracy, precision, sensitivity, and F-measure [40]. This method tries to prioritize the data sensed in the IoT network and does not pay attention to the quality of service parameters.

3. The Proposed Method

In this paper, in order to provide a reliable data transfer protocol in the context of healthcare, a multiobjective method is presented. Given that the selection of reliable agents among the devices in the IoT network in order to meet the quality of service criteria is a complex issue, in this paper, the multiobjective genetic optimization algorithm is used. The multiobjective genetic optimization algorithm has tried to find the optimal path by creating a tradeoff between the quality of service criteria. The witness of the optimality of the selected algorithm in the proposed method is acquired results and comparison with other works in terms of quality of service criteria and improvements.. The proposed method uses a multistep information transfer approach to send information to access points. Access points in the proposed network are connected to nursing stations to send information in order to be analyzed by physicians and specialists. The proposed method uses a multiobjective genetic algorithm to find the optimal nodes in each step of information transfer. The proposed method tries to determine the optimal path for packet transmission based on the selection of reliable agents using the multiobjective genetic optimization algorithm. The proposed method, also, uses the backup path to deal with possible failures in the optimal path. The backup path is in the second optimal solution in the repository of the multiobjective genetic optimization algorithm which can be considered as innovation and significance of the proposed method. Since the fitness function used in the proposed method uses the criteria of the distance between nodes, distance to access point, link quality, and reliability degree, the optimal nodes are selected as reliable factors in the proposed method. In order to ensure the reliability of the proposed method, in the first step, two reliable nodes are selected and the path from the optimal node is selected as the main path and the second optimal node is selected as the backup path. The prerequisites of the proposed method will be described below. The overall architecture of the proposed method is shown in Figure 1.

3.1. Proposed IoT Network Model. As mentioned in the proposed method, to find a secure path in the context of IoT networks, four parameters are discussed: distance between nodes, distance between intermediate nodes to the base station node, link quality, and degree of reliability. These parameters play a decisive role in the process of selecting the next hop nodes, and improving these parameters will improve other goals in the network. The proposed method

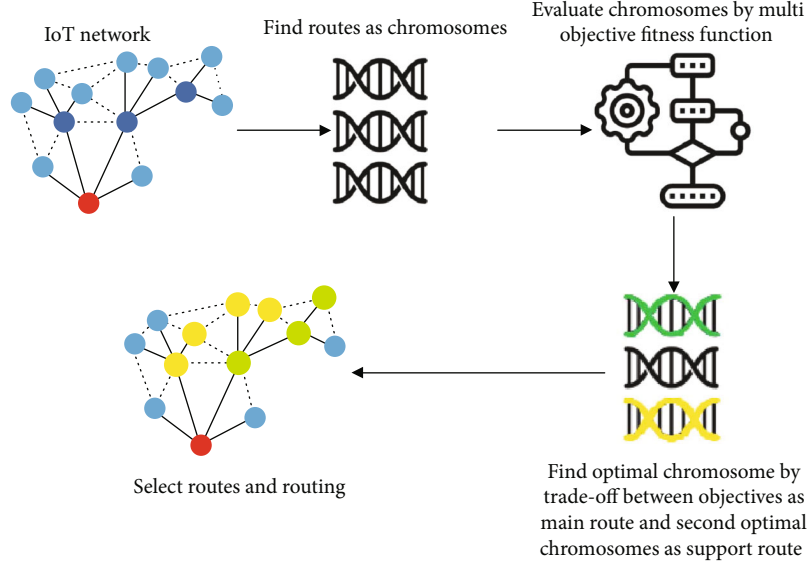


FIGURE 1: Overall architecture of the proposed method.

tries to find a reliable path in the IoT network by optimizing these parameters in the form of a multiobjective fitness function, and then, the parameters used in the proposed method are modeled. A flowchart of the proposed method is presented in Figure 2.

3.1.1. Distance between Nodes $D(K, K + 1)$. In the IoT network, intermediate nodes must send sensed data from the environment to base stations. When the source node, the node that currently holds the packets, sends the data, it tries to send the packets to the nearest node in its neighborhood. Sending packets in the shortest distance between nodes not only reduces the delay of data transfer between the source and the base station but also increases the reliability of the route. The distance model between nodes is expressed in equation (1) as follows:

$$D(K, K + 1) = \min \left(\sum_{K=1}^N (\sqrt{x_K - x_{K+1}})^2 \right), \quad (1)$$

where $D(K, K + 1)$ is the distance between the current nodes and the nearest node in the next hop, K is the number of neighboring nodes of the current node, N is the total number of nodes in the IoT network, x_K is the current node position, and x_{K+1} is the position of the next node.

3.1.2. Distance of the Next Node to the Base Station $D(K, BS)$. In IoT networks, the equipment can act as a relay between source and destination nodes. In order to select the optimal route between the source node and the base station, the nearest route can be less general and more reliable. The distance from the next node to the base station can determine the convergence of the path to the base station. In fact, if the distance from the next node to the base station is less than the distance from the current node to the base station, then, the selected path converges in the direction of the base

station, and then, the current node from its neighbors is the node with the shortest distance to the base station. Now, we can select a safe path. The model of the distance between the next node and the base station is expressed as equation (2) as follows:

$$D(K + 1, BS) = \min \left(\sum_{K=1}^N (\sqrt{x_{K+1} - x_{BS}})^2 \right), \quad (2)$$

where BS represents the base station and x_{BS} represents the base station position.

3.1.3. Link Quality. In the proposed method, the link quality is considered as a criterion for estimating the number of steps required to transfer data to the base station. The link quality is used with a metric called ETX (expected transfer) to indicate the estimated number of steps between a node and the base station at the time of data aggregation. In other words, for a clustered node, ETX is the estimated total cost of collecting data from the cluster member nodes that belong to it and transferring of the aggregated data to the hole in several steps. Obviously, the lower the ETX for a node, the fewer the steps required to send data and the better the link quality. Link quality modeling is shown in equation (3) as follows:

$$ETX(K + 1, BS) = \min \sum_{i=1}^K \sum_{j=1}^{BS} H(S, K) + \left(\frac{D(K + 1, BS)}{R} + 1 \right), \quad (3)$$

where $H(S, K)$ is the number of goats passed from the source node to the current node and R represents the range of nodes in the IoT network.

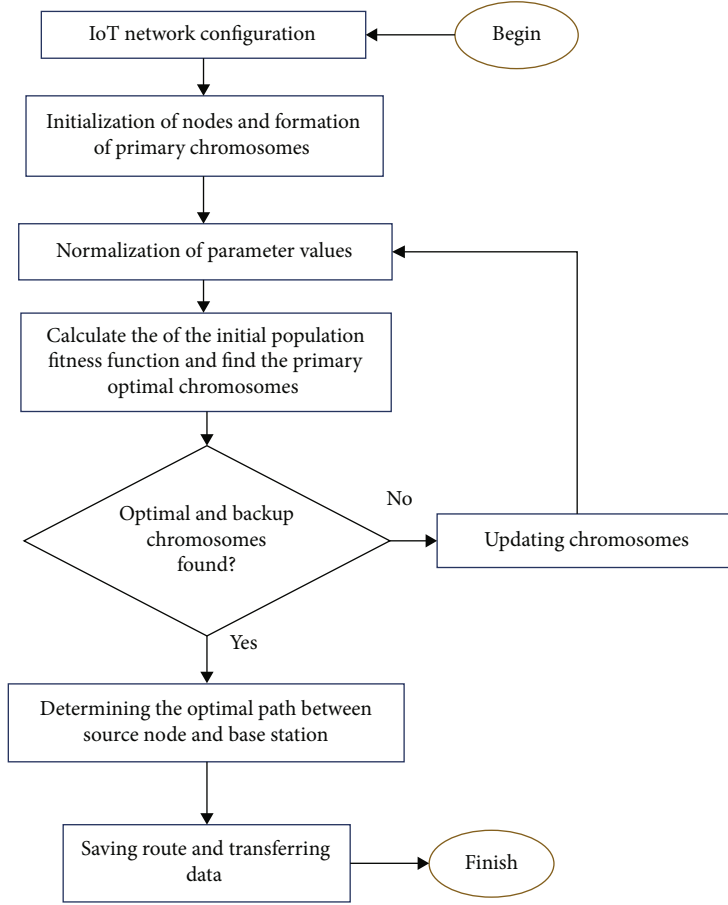


FIGURE 2: Flowchart of the proposed method.

3.1.4. The Degree of Reliability of the Route. In the proposed method, in order to find a safe path for transferring information between the destination node and the base station, the degree of reliability of the nodes in each step is checked. In order to transmit packets to neighboring nodes, the current node must select the node with the highest degree of security in the neighborhood to create a secure path between the destination node and the base station. The degree of reliability in the proposed method is quantified by equation (4) as follows:

$$P(K, K + 1) = \min \left(\sum_{i=1}^M \left(1 - \frac{\text{PRR}_{(K,K+1)}}{\text{PDP}_{(K,K+1)}} \right) \right), \quad (4)$$

where $\text{PRR}_{(K,K+1)}$ is the rate of receiving packets between the current node and the neighboring node and $\text{PDP}_{(K,K+1)}$ is the rate of sending packets between the current node and the neighboring node.

The proposed method, based on the mentioned parameters, selects the optimal node in the neighborhood and the IoT network.

3.2. Multiobjective Genetic Algorithm. The genetic algorithm begins with the random production of the initial population as some random solutions to the problem, and in an iterative process, these solutions evolve and approach the optimal

solutions. Thus, genetic algorithms are greatly influenced by the operators that create the newly evolved population. A genetic algorithm is a random search technique that increases the likelihood of selecting optimal solutions. This algorithm includes a population of solutions which are considered as chromosomes. Each solution, to be presented as a chromosome, requires a coding method in which genes are formed based on the application of the problem and then together form chromosomes [41].

Each iteration in a genetic algorithm involves many operators that begin by assessing the fitness of chromosomes. Subsequent operators that are important include crossover, mutation, and selection. The crossover operator enables the genetic algorithm to generate a new generation with solutions resulting from the interconnection of chromosomes from two selected parents, resulting in the production of one or more offspring through the integration of specific gene houses from the parents. The crossover operator selects the cut and merges the location of the two chromosomes based on the probability of P_{cross} . Equation (1) shows the selection of the crossover point on the chromosomes [41].

$$\text{Crossover} = (P_{\text{cross}} * (G_{\text{max}} - G_{\text{min}})), \quad \forall i = 1, 2, \dots, M - 1, \quad (5)$$

where crossover is the chromosome configuration, the G_{\max} parameter is the maximum number of genes per chromosome, the G_{\min} parameter is the minimum number of genes per chromosome, and P_{cross} is a random number in the range (0,1). The fitting operator is used to diversify the initial population. The mutation operator sporadically updates some of the genes on the chromosome to increase chromosome fitness.

The mutation operator selects the location of the gene on the chromosome based on the probability of P_{mutate} . Equation (2) shows the choice of gene location on the chromosome [41].

$$\text{Mutation} = (P_{\text{mutate}} * (G_{\max} - G_{\min})), \quad R \text{ is a rand in } [0, 1], \quad (6)$$

where the mutation parameter indicates the gene to be mutated and P_{mutate} is a random value in the range [0,1].

The selection operator also transmits the best chromosomes from the current population to the next generation. In genetic algorithms, a number of possible solutions are first randomly generated as the initial population. In chromosome coding and gene representation, selection plays an important role in the production of the initial population. In the next step, the degree of competency of each initial population is measured based on the evaluation function. The evaluation function is a measure of the evolution of existing chromosomes. Then, a number of solutions are selected as the parent based on the degree of competency and create new children as new solutions. New children are transferred to a new population and create a new generation, and the same process is repeated for the new generation. The iteration of the genetic algorithm continues until the termination condition is met.

3.3. Initial Population Coding. The first step in using a genetic algorithm is to encode and generate a random primary population. Coding refers to how genes are quantified on chromosomes, where the arrangement of genes together will lead to a solution for the routing problem. In genetic algorithm-based routing methods, chromosomes include nodes that exist between the source and destination nodes. These nodes are selected as relays in the path between the source and destination nodes, which is considered as a solution. Table 1 shows an overview of coding based on intermediate relay nodes.

As shown in Figure 1, each of the genes in the chromosomes in the proposed method represents an intermediate node between the source node and the destination node. The number of genes on all chromosomes must be the same. Therefore, the number of genes must be part of the number of nodes in the network. In the proposed method, the number of available genes is obtained from equation (7) as follows:

$$N_M = \frac{x_S - x_{BS}}{\sum_{i=1}^N (R_i/N)} + 1. \quad (7)$$

TABLE 1: How to code primary chromosomes based on intermediate nodes.

N_1	N_2	N_3	N_4	N_5	N_6	...	N_M
10	14	21	11	8	7	...	4

According to equation (7), it can be said that the number of genes in the proposed method is determined by dividing the direct distance between the source sphere and the base station by the average range of nodes in the network. Since the existing IoT network nodes are heterogeneous, the communication range of the nodes may be varied. Therefore, in the proposed method, the average communication range of all nodes in the network is used.

3.4. Proposed Fitness Function. In order to formally define the evaluation function in the proposed method, we assume that the current node is represented by index i and the neighboring nodes are represented by index j . For this purpose, considering the modeling of optimization methods for multiobjective genetic algorithms, we consider the following limitations in the proposed method.

- (i) The sum of the distances between nodes in the optimal path should not be more than a fixed value. This limit is set so that the number of steps in the path is not large. If the threshold of distances between nodes is too large, all the nodes in the network may be in the same path, which greatly affects the performance of the proposed method
- (ii) The number of steps of sending data between nodes in the optimal path should not exceed the quality of the estimated link. This constraint prevents looping and adding additional nodes in the path and ensures that the proposed method finds the shortest path in the network to transfer data from the destination node to the base station
- (iii) The initial degree of reliability of the nodes is equal to a fixed value and not more than that. Reliability is updated as data transfer between nodes increases. Given that in the proposed method, the main focus is on increasing the degree of reliability between nodes in the IoT, nodes must have a constant and uniform initial degree of reliability in order to ensure fairness in data transmission in the proposed methods
- (iv) The total delay of packet transfer on the route should not be more than a fixed value. Critical messages on the network must reach the base station within the timeframe; otherwise, they may disrupt the intended applications in the IoT

Since the goals in the network may be conflicting and the improvement of one goal reduces the optimization of the other one, the usual criteria for IoT are insufficient. Thus, multiobjective criteria are considered to find the right path

from the source node to the base station. The multiobjective genetic algorithm optimization method tries to create a balance between the goals in the network that may be contradictory or compatible, and more importantly, the optimality of all goals is considered. Therefore, the mentioned parameters are considered for the multiobjective function in order to find the most optimal path between the source node and the base station. Finally, the summative evaluation function is shown in equation (8) as follows:

$$\begin{aligned}
F = \text{Min} \quad & \sum_{i=1}^n \sum_{j=1}^k D(K+1, BS) - D(K+1, BS) \\
& - ETX(K+1, BS) + P(K, K+1) \\
\text{s.t.} \quad & \sum_{j=1}^k D(K+1, BS) \geq \alpha \\
& \sum_{i=1}^n D(K+1, BS) \leq \beta \\
& \sum_{i=1}^k ETX(K+1, BS) \leq \gamma \\
& \sum_{i=1}^k ETX_i \leq \delta \\
& \sum_{i=1}^k \text{delay}(S, BS) \leq \omega.
\end{aligned} \tag{8}$$

In equation (8), i is the number of nodes, j is the number of neighboring nodes, α is the upper limit of the distance between nodes, β is the upper limit of the distances between nodes and the base station, γ is the total initial confidence of the nodes, δ is the maximum number of steps in the optimal path, and ω is the maximum delay in the IoT network. According to equation (8), in each round of the proposed multiobjective genetic algorithm in the path selection step, the node that minimizes the value of the F function is selected as the first optimal neighbor node. Also, the node that fits in the second place is selected as the optimal node in the backup path. The data transfer process is then sent from the current node to the base station. If an error occurs in the optimal path and a node leaves the transfer process, the data transfer will start from the backup path. The selected path based on balancing the goals of the IoT network is the shortest path with the shortest distance between nodes which will cause the least amount of delay.

On the other hand, due to the fact that the values of the parameters used in the fitness function do not match and the scale of these parameters is different from each other, combining these parameters in the form of a function can result in incorrect results. In other words, since the values of the parameters are in different ranges with different scales, the parameter that has a higher value can have more parameters than the values with lower values. Therefore, it is necessary to convert the parameters and map the values related to

the parameters in a certain range, which is called normalization. Normalization maps values related to different parameters in the range of [0,1] so that the parameters do not have a negative effect on the results. The problems related to the scale of these parameters are eliminated. In fact, after normalization, the values of all parameters are relatively between zero and one and various units for different parameters will not affect the results of weight determination for chromosomes. Various normalization methods have been introduced in journals—the most famous of which is the Z-score normalization [33]. In the proposed method, Gaussian normalization has been used in order to eliminate the negative effects of parametric values on the scale. The Gaussian normalization is introduced in equation (9) as follows:

$$\text{Normalized - data} = \frac{\text{data} - \text{mean}(\text{data})}{\text{std}(\text{data})}. \tag{9}$$

In equation (9), normalized data of parameter values after normalization process, data of parameter values before normalization, mean (data) mean of values of each parameter, and std (data) of the standard deviation of values of each parameter. The output from the normalization phase will be used as the input of a multiobjective genetic algorithm.

4. Implementing the Proposed Method

The data used in this paper are obtained from IoT network simulation in MATLAB software. This article does not use standard datasets stored in data warehouses. Instead, a standard network with 100 nodes is implemented using standard network parameters. The implemented nodes are randomly distributed in the network space. These nodes have the ability to receive and send data. Each node has a defined communication range in which it can communicate with other nodes. By transferring information in the network, the values of the variables used in the proposed method are extracted from the network and used to apply the proposed model.

We start the implementation of the proposed method with the initial configuration of nodes in the IoT network and the distribution of nodes in the monitored environment in MATLAB software version 2019. We consider the monitored environment to be 100×100 space in which 100 sensor nodes are randomly scattered. The number of sensors can be adjusted according to different scenarios, and this number can be changed in order to compare the proposed method with other methods available in publications. Other parameters related to network configuration are considered according to the standards mentioned in the publications. The proposed network is implemented in an environment of 100×100 . The proposed IoT network parameters are shown in Table 2. Figure 3 also shows the initial configuration of the wireless sensor network based on the proposed scenario.

As shown in Table 1, the IoT network is formed according to the random distribution of nodes and based on the values of the parameters in Table 2. A base station has been installed in the monitored area. In the first step of the hole

TABLE 2: Initial parameters of the proposed sensor network.

Parameter	Value
Network dimensions	100*100
Number of nodes	100
Base station coordinates	(100,100)
The initial degree of reliability of the nodes	0
The initial probability of selecting a neighbor node	0.01
Maximum number of rounds	100
Data package length	40
Number of packages sent per hop	10
Length of the routing package	100
Radiation range	5

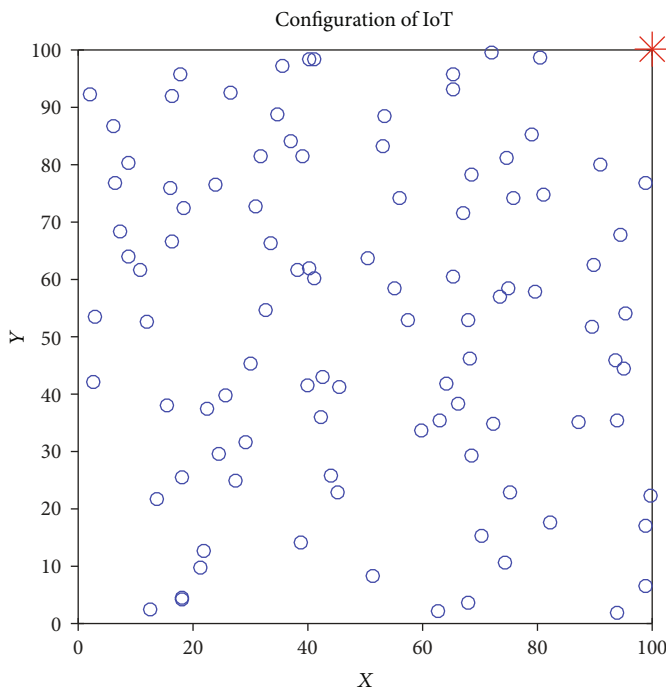


FIGURE 3: Initial configuration of the proposed IoT network.

node simulation, by sending a routing package in the form of a “Hello” message, it tries to obtain information about the Hasim node in the network. Each node that receives this message immediately sends RREP routing response packets to begin the process of route selection and network security.

4.1. Primary Chromosome Quantification. As mentioned in previous chapters, the proposed method uses a multiobjective genetic algorithm to route in the IoT network. One of the differences between the proposed method and the simple genetic algorithm is the use of a multiobjective fitness function. In order to implement the proposed method in the proposed scenario, the initial solutions must first be quantified. Since the solutions of the proposed method are applied as chromosomes to the proposed genetic algorithm, they must be encoded in the standard chromosome defined for the

proposed method. The chromosomes of the proposed method, as discussed in Section 3, are arranged based on the number of nodes in the path. Thus, in Table 3, a part of the initial population is shown in the proposed method.

As shown in Table 3, the initial population is adjusted according to the number of optimal path steps based on equation (7). Therefore, in the next step of implementing the proposed method, we will implement the proposed genetic algorithm on the initial population.

4.2. Implementation of the Proposed Genetic Algorithm. To implement the proposed method, in this section, we first evaluate the initial population. The initial population, as shown in Table 3, consists of a number of chromosomes whose size is predicted to be equal to the number of steps. Each of these genes takes on a value that represents the node in the optimal path. According to the objectives of this paper, the proposed multiobjective genetic algorithm uses a multiobjective fitness function to evaluate the initial population. In addition to the distance between nodes and the distance between nodes with the base station, the proposed proportionality function also examines the link quality and the degree of path reliability. Table 4 shows the values of general fitness and partial factors for the initial population.

As shown in Table 4, for each chromosome, the values of the overall fitness function and the fitness function are calculated based on multiple evaluation factors. Table 4 shows only 5 chromosomes from the original population, and to show the values of the other chromosomes in the original population, we use the distribution graph of the values of the evaluation function in the search space. Figure 4 shows the distribution of the values of the overall proportionality function of the initial population, which is arranged in descending order.

As shown in Figure 3, the values of the overall fitness function are calculated for the initial population. The overall fitness function represents the overall quality of a chromosome and examines the proposed routing from all aspects of the network. According to Table 1, it can be seen that some of the randomly selected primary solutions have a good proportion value but some other chromosomes in the initial population do not have a good proportion value and should be removed from the initial population. The figure shows that the most optimal chromosome has a proportionality value of about 0.0308. In the next step, the selected chromosomes are transferred to the fitting operator. In the fitting operator, a shear point is used and the fitness values are checked for each of the fitted populations and the population with the best fitness value is transferred to the jump operator as the output population. In the proposed method, we use this operator for creating an expert population among the new population. In fact, in the proposed method, the new population obtained from the fitting operator will have near-optimal proportion values and chromosomes that have nonoptimal proportion function values will not enter this population. In addition to generating new populations and diversifying the generation of previous chromosomes, this operator accelerates the convergence of new populations toward optimal points in terms of research objectives.

TABLE 3: Sample of the initial population.

	G_1	G_2	G_3	G_4	G_5	G_6	G_7	G_8	G_9	G_{10}	G_{11}	G_{12}	G_{13}	G_{14}	G_{15}
CH1	4	3	17	15	17	8	20	7	14	10	9	1	17	22	24
CH2	1	4	6	3	2	8	13	15	9	23	11	14	12	23	18
CH3	3	1	2	10	11	3	15	18	7	6	13	22	2	10	11
CH4	14	1	3	11	7	2	5	21	6	8	14	20	9	11	10
CH5	18	3	14	10	25	4	9	2	20	12	18	5	11	10	22

TABLE 4: The values of the initial population fitness function.

Chromosome number	Value of overall fitness function	Value of fitness function for node intradistance	Value of fitness function for distance between nodes and base station	Value of fitness function for link quality	Value of fitness function for reliability
1	0.0316	0.0164	0.0111	0.0076	0.4430
2	0.1189	0.0659	0.0652	0.0659	0.4431
3	0.0551	0.0275	0.0185	0.0183	0.4430
4	0.0217	0.0330	0.0222	0.0282	0.4431
5	0.1770	0.0275	0.0185	0.0127	0.4431

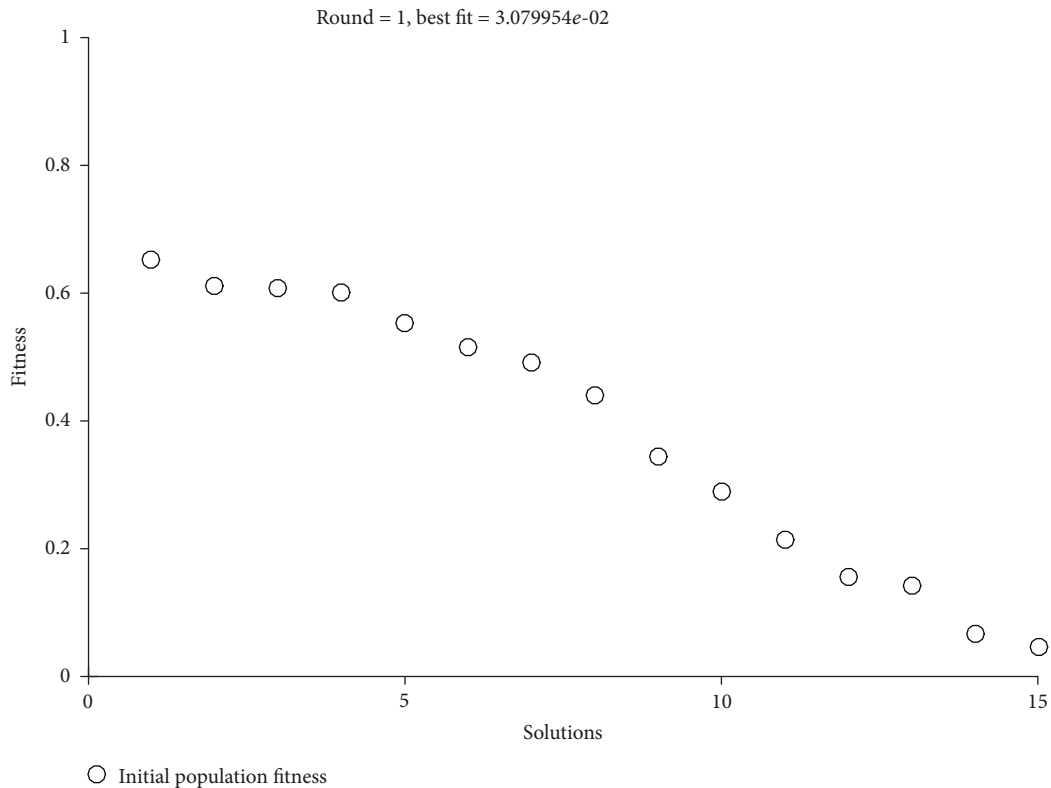


FIGURE 4: Values of the overall fitness function of the initial population.

After fitting the initial population and producing a new population close to optimal, in the next step, the jump operator is applied to the new population and slightly increases the diversity of the new population compared to the previous population. Due to the fact that the proposed method uses the adaptive fitness operator, variations in the fitted population may lead to inverse results in the values of the fit-

ness function. Figure 5 shows a graph of the dispersion of the fitness function in the initial population and the new population resulting from crossover and mutation.

As shown in Figure 5, the values of the overall fitness function of the solutions are optimized for fitted chromosomes from the original population. Given that the proposed proportionality function is introduced as a minimization

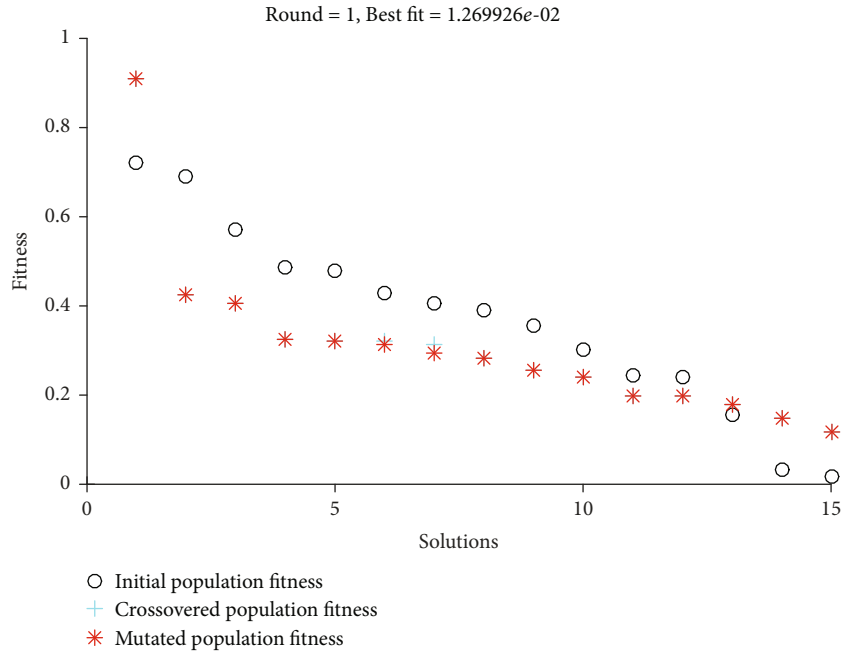


FIGURE 5: Values of the fitness function of the initial population after the application of genetic operators.

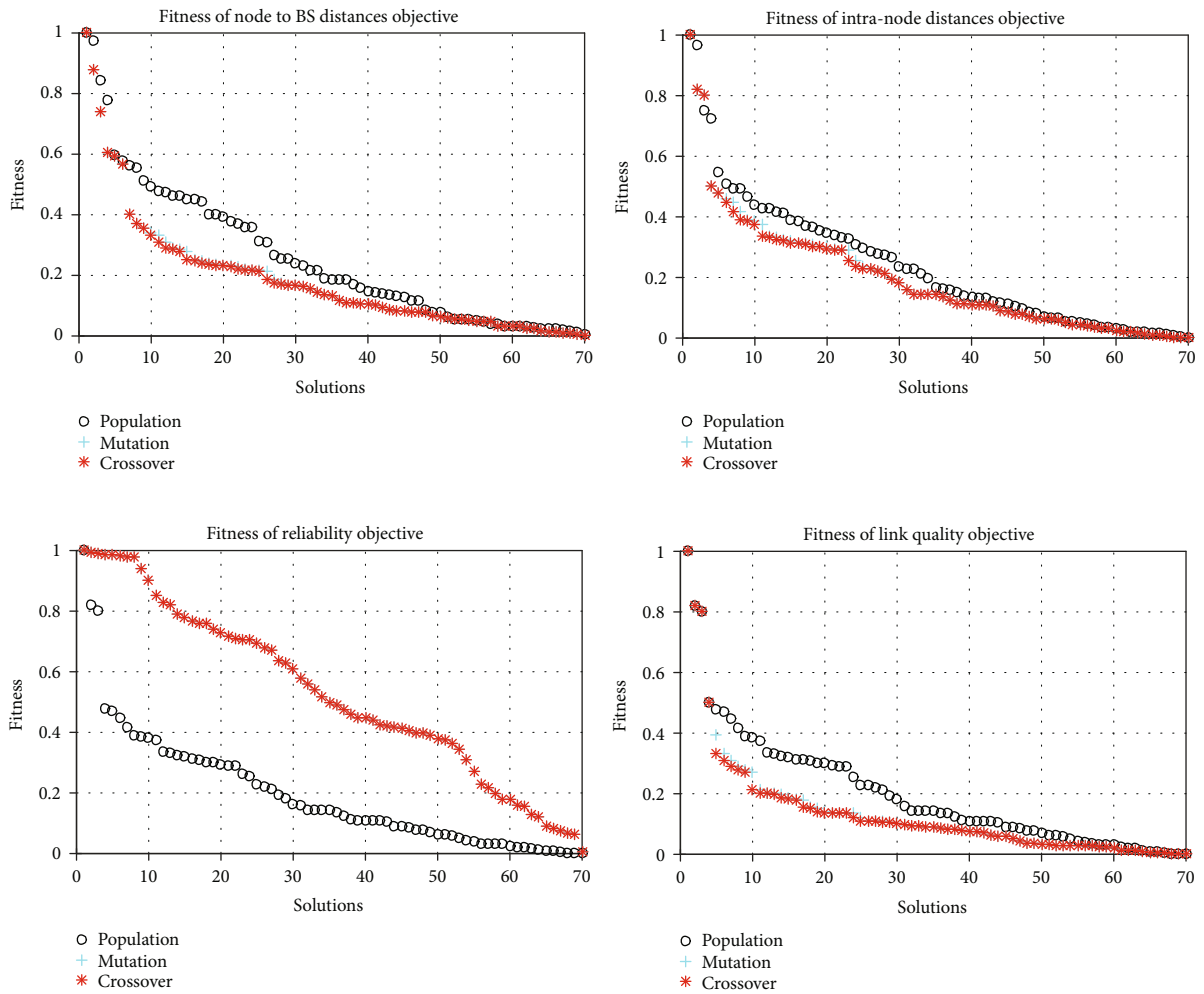


FIGURE 6: Fitness values on multiple criteria after applying the crossover and mutation operator.

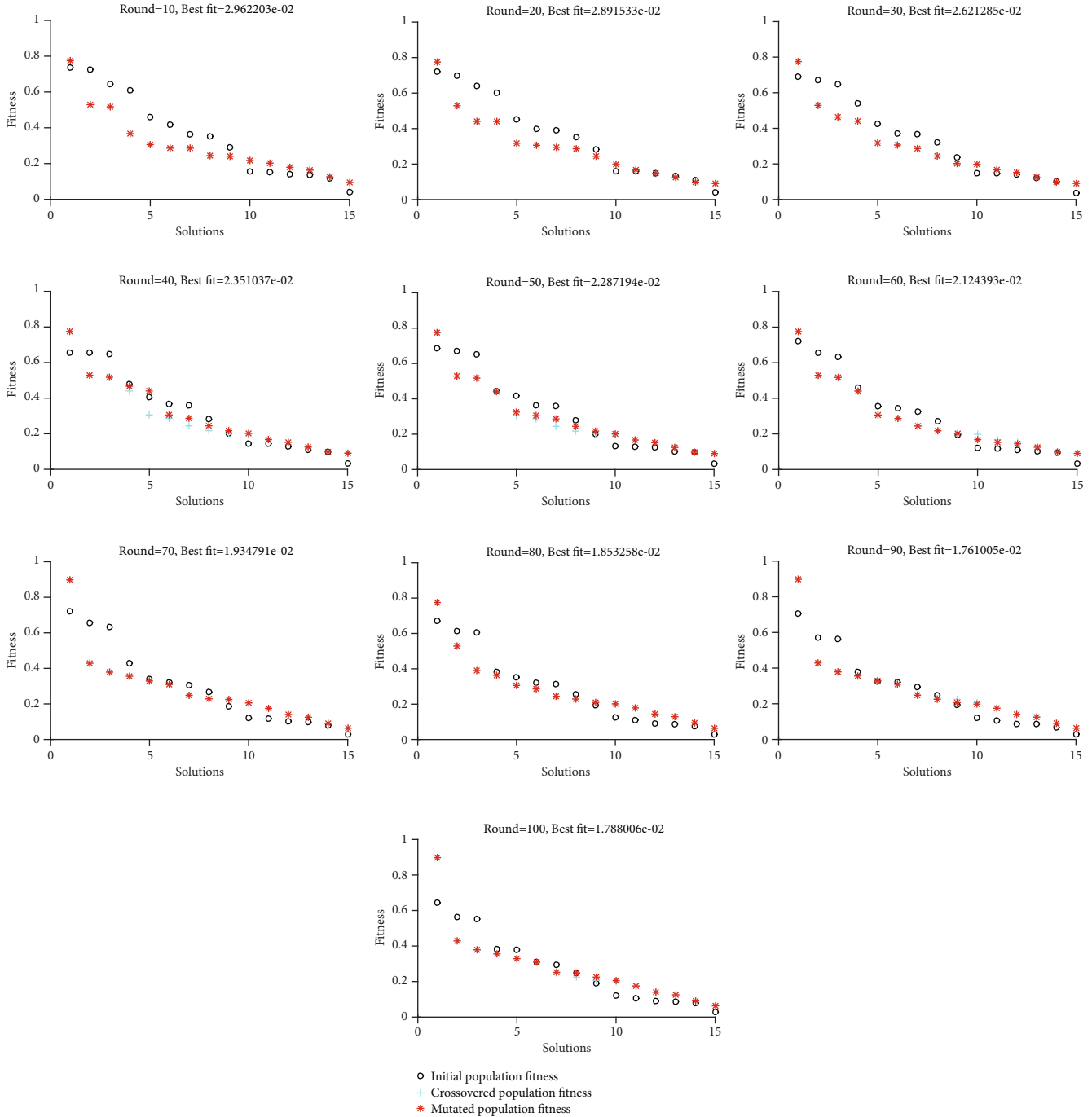


FIGURE 7: Repetition process in the proposed genetic algorithm.

problem consisting of three minimization components, the lower the value of the overall proportionality function, the higher the quality for the obtained chromosomes. Hence, the value of the overall fitness function in the proposed method approaches the optimum value by decreasing the values for each chromosome. Figure 4 also shows that the value of the fitness function for chromosomes is reduced and improved by applying adaptive fitting operators. Due to the fact that the proposed method uses a multiobjective fitness function, the fitting operator affects each of the cri-

teria used in the fitness function. Therefore, Figure 6 shows the changes of adaptive crossover and mutation operators on the criteria used in routing in the proposed method.

As shown in Figure 6, the values of the fitness function for multiple criteria in the network are improved by the fitting operator. Since this criterion is the distance between nodes, the distance of nodes to the base station, and the quality of the link concerning the proposed proportionality function as a minimization criterion, according to Figure 5, the diagrams related to these criteria can be seen as it is less

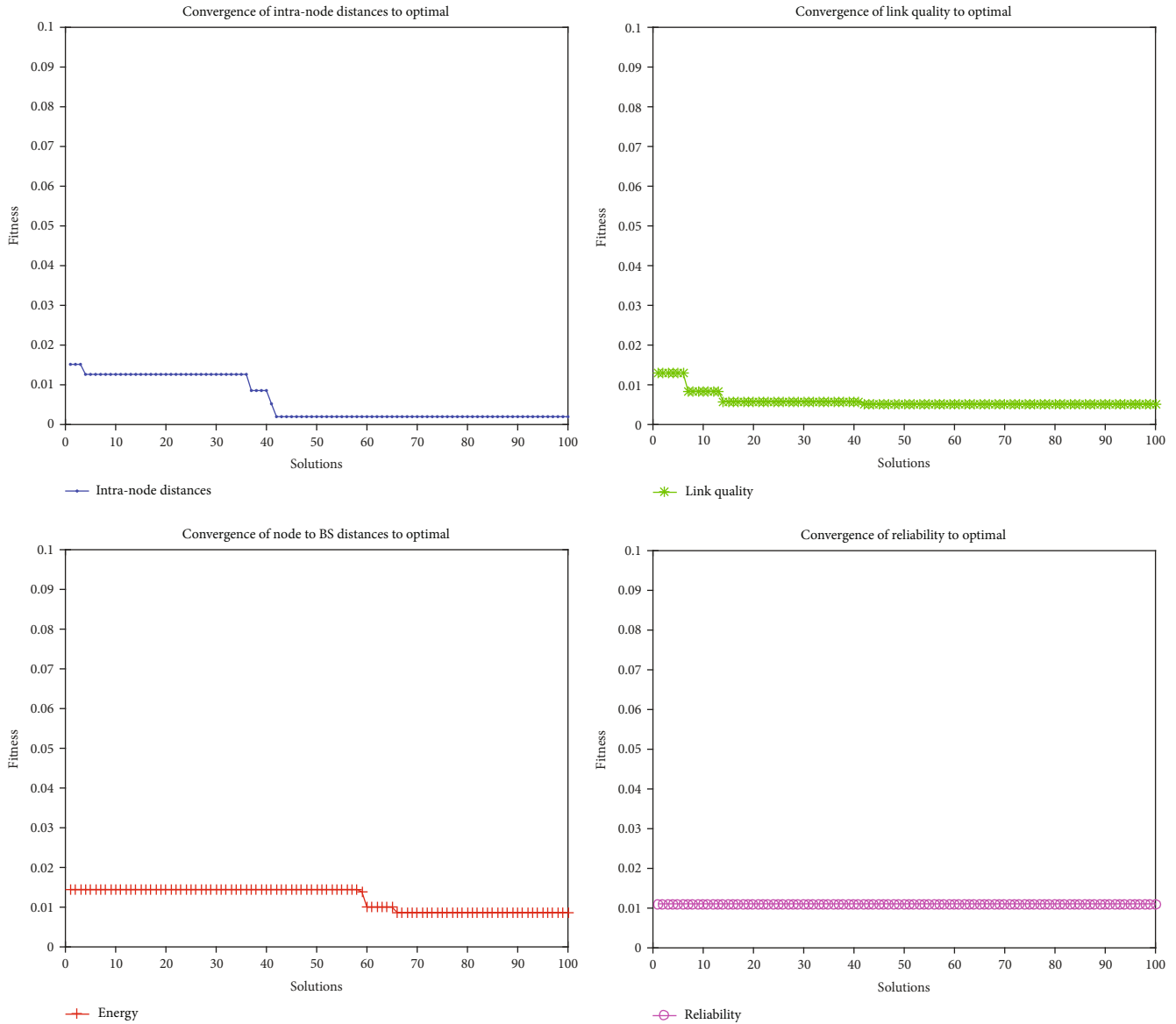


FIGURE 8: Convergence of the proposed genetic algorithm towards optimal points for the purposes of the fitness function.

TABLE 5: Final optimal chromosome.

	G ₁	G ₂	G ₃	G ₄	G ₅	G ₆	G ₇	G ₈	G ₉	G ₁₀	G ₁₁	G ₁₂	G ₁₃	G ₁₄	G ₁₅
CH1	1	3	2	6	7	8	9	10	5	19	23	17	19	22	24
CH2	1	5	85	77	99	41	92	37	97	89	96	74	25	14	32

active than the main chromosomes. Also, since this degree of confidence in the proposed proportionality function is expressed as a maximization criterion, according to Figure 5, it can be seen that the graph related to this criterion is higher than the main chromosomes after the operators are applied. The proposed genetic algorithm is based on the new population as well as the fitting and mutation operators until the stop condition is met. In this research, the condition for stopping is 100 repetition generations, which is shown in

Figure 7, the results of the general fitness function in every ten repetition steps.

As shown in Figure 7, the proposed genetic algorithm continues to operate with respect to the genetic operators of fitting and mutation, increasing the values of the overall fitness function from 0.0289 to about 0.0178. These values indicate the evolution of the population in the process of replicating the proposed genetic algorithm and determining the best population based on the proposed method. The

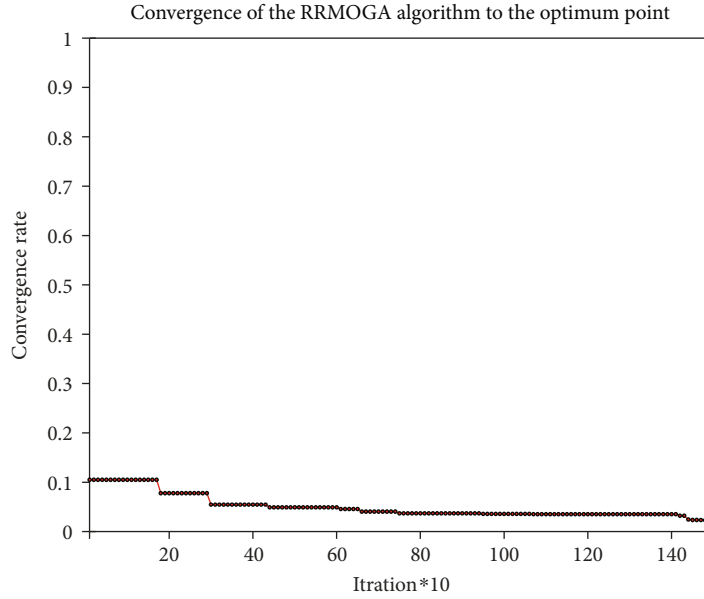


FIGURE 9: Convergence of the multiobjective genetic algorithm towards the optimal point.

TABLE 6: Average values of evaluation criteria.

Criteria	Lifetime	Delay	Data delivery rate	Reliability
Average	1400	0.0523	99.9	99.44

proposed genetic algorithm approaches the optimal points step by step and, in Figure 8, converges the four criteria of the distance between nodes, node distance to the base station, link quality, and degree of reliability used in the fitness function in the multiobjective genetic algorithm in the last generation of iteration.

As shown in Figure 8, the proposed method converges to the optimal point based on the objectives introduced during the algorithm. Thus, the final population found by the proposed multiobjective genetic algorithm is the near-optimal solution. Table 5 shows the final optimal chromosome as the primary pathway and the second optimal chromosome as the backbone for routing.

As shown in Table 5, the final solution of the problem is determined based on the proposed genetic algorithm and the criteria specified in the proposed method. Finally, the general tendency of the multiobjective genetic algorithm method towards the optimal point during the IoT network application time is shown in Figure 9.

4.3. Evaluating the Proposed Method. The evaluation of the proposed method is done in order to evaluate the quality of the proposed method and to provide the improvement created by the proposed method based on the initial problem. Given the popularity of IoT networks, there are a variety of criteria to evaluate. Evaluation criteria in IoT networks vary according to different applications. Therefore, in this study, given that we seek to increase the degree of reliability, throughput, and data delivery rate and to reduce network latency, we will be satisfied with these four criteria. Thus,

we first show the main values of the evaluation criteria in Table 6.

As shown in Table 6, the proposed method has averaged the appropriate evaluation criteria. Figure 10 shows the average energy consumption of nodes in the IoT network.

As shown in Figure 10, the average energy consumption of nodes in the proposed IoT network increases in a balanced way according to the selection of optimal nodes in each step. Thus, it can be concluded that the energy of the sensor nodes embedded in the equipment is exhausted at almost the same time and the lifetime that the network can have its maximum value. Network lifetime refers to the period of time that the network is available and does not interfere with the aggregation of network data. Therefore, the time of energy depletion in a number of nodes in the network in a way that we are not able to continue the operation of the network with the remaining nodes can be considered as the lifetime of the network. Figure 11 shows the network lifetime in the proposed method.

Figure 11 shows that in the proposed network, the network lifetime reaches 1400 cycles and the death of the first node occurs after 1023 repetitions. In wireless sensor networks, with the death of a node, all the paths leading to this node are blocked and they have to use backup paths. Thus, by using a backup path in the proposed method, data transfer in the IoT network continues its normal process until no optimal path can be found for data transfer, and consequently, the degree of reliability of the proposed routing protocol will be high. Figure 12 shows the reliability diagram of the proposed method during data transfer in the proposed IoT network.

As shown in Figure 12, the reliability of the proposed method is high owing to the use of the optimal path and the choice of backup path throughout the simulation time. Therefore, it can be said that the proposed method has provided a reliable approach for the transfer of medical data in the healthcare system.

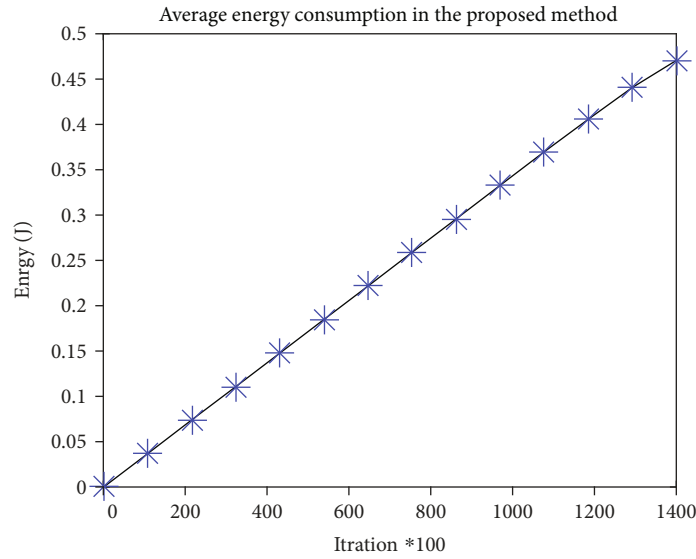


FIGURE 10: Average of energy consumption in the network.

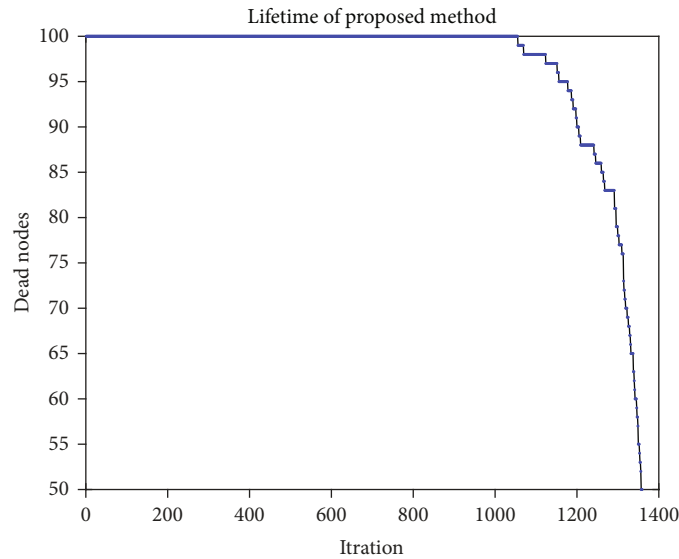


FIGURE 11: Node lifetime in the proposed IoT network.

Another criterion used to evaluate the proposed method is the data delivery rate criterion in the proposed IoT network. The data delivery rate criterion is the rate of packets sent per unit of time and received at the destination. In other words, the rate of data collected that has safely reached the nursing station per unit of time in the IoT network is based on the healthcare system and is called the network data delivery rate. Figure 13 shows the passing criteria of the proposed method.

As shown in Figure 13, the proposed method tries to escape bottlenecks and create a secure path to send data to the hole nodes with respect to optimal routing. Therefore, the data delivery rate in the proposed network is high and its average is 99.9%. The last criterion utilized for evaluation in the proposed method is the end-to-end delay of nodes in

the network. Given that the transfer time is for fixed nodes, the main reason for the delay in the end-to-end transfer is the distance between nodes. Since in the proposed method, according to the multiobjective fitness function, data transfer between nodes occurs in the shortest distance, the end-to-end delay will be the least. The total network latency, which consists of the sum of the end-to-end latency between nodes, is shown in Figure 14.

As shown in Figure 14, in the proposed method, the end-to-end latency between nodes increases in a balanced way indicating the minimum distance and minimum delay for sending packets between nodes.

4.4. Comparing the Proposed Method with Previous Works. The development of the use of the IoT infrastructure in

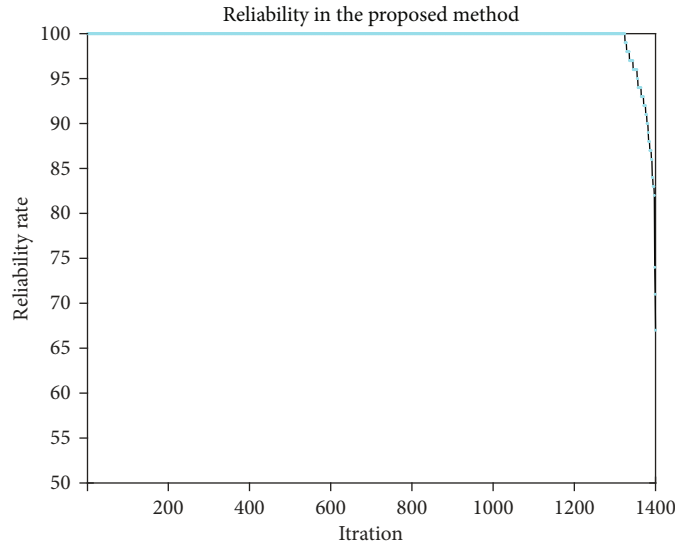


FIGURE 12: Degree of confidence in the proposed method.

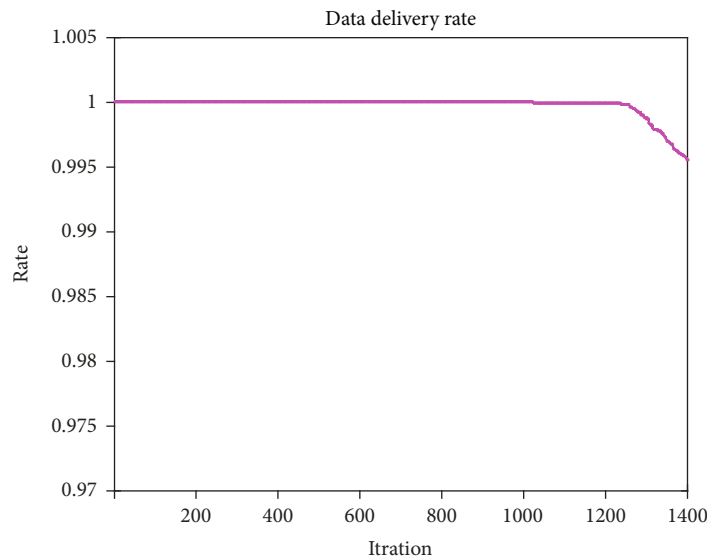


FIGURE 13: Data delivery rate of the proposed method.

healthcare systems has led to extensive research into routing in IoT networks. In the continuation of this part of the article, in order to validate the proposed method, we will compare it with the previous methods in terms of reliability, lifetime, latency, and data delivery rate in the network. The most important criterion that the proposed method focuses on is the degree of reliability in the information transmission path. So, we compare RRMOGA with RRDLA [42], DETR [43], and REER [44] in terms of reliability. Figure 15 shows a comparison of the degree of reliability in the proposed method with other previous methods.

As shown in Figure 15, the proposed method has a higher degree of reliability than the previous methods due to the selection of reliable agents and the use of a backup path to deal with possible failures in the optimal path.

We compare the proposed method with the basic methods of AODV [45], LABILE, and REL [46] algorithms in terms of the mentioned criteria. Figure 16 represents a comparison between the proposed method and previous methods considering the length of live nodes in the network.

As shown in Figure 16, the proposed method has more live nodes than the previous methods. Therefore, it can be concluded that due to the use of the multiobjective fitness function, the network life in the proposed method is longer than in other previous methods. Furthermore, in Figure 17, the proposed method is compared with previous methods in terms of the data delivery rate.

As shown in Figure 17, the proposed method has a higher delivery rate than other related methods. The data delivery rate in the proposed method is higher due to the

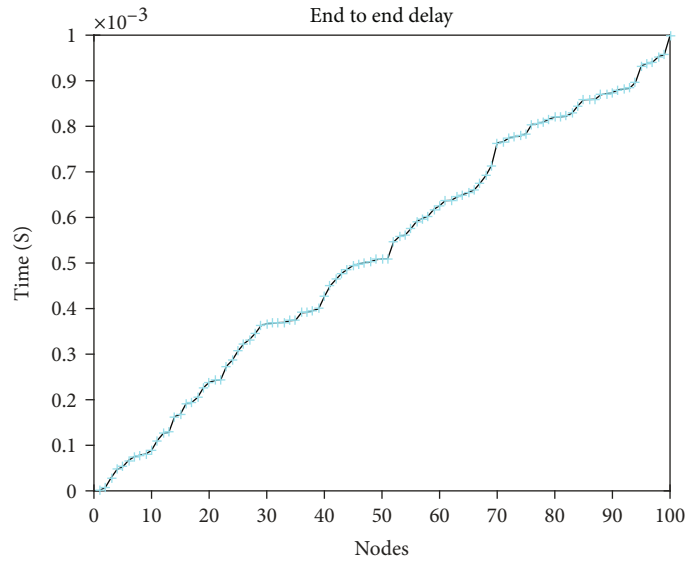


FIGURE 14: End-to-end delay of nodes in the proposed IoT network.

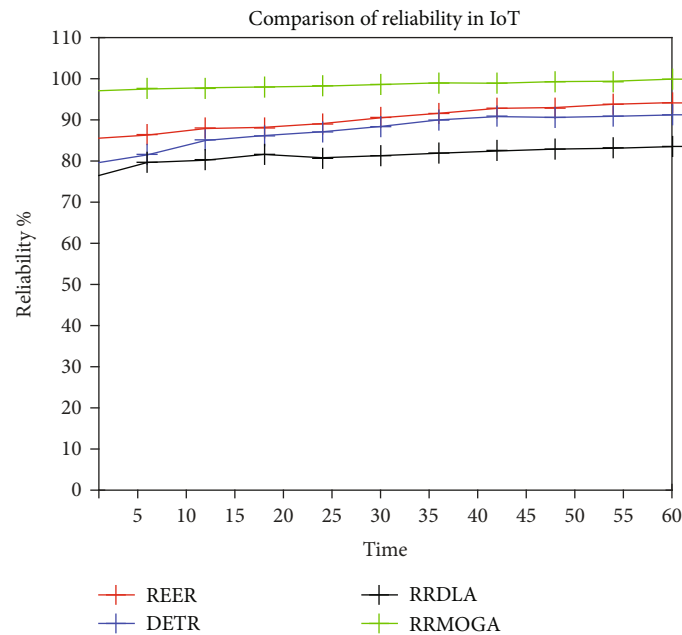


FIGURE 15: Comparison between the proposed method and previous methods in the aspect of reliability.

balance between the basic factors in the network based on the multiobjective proportionality function. Another criterion that shows the improvement of the proposed method compared to other existing methods is the overall delay of the method in data transfer. Figure 18 compares the proposed method with previous methods in terms of packet transfer delay.

As shown in Figure 18, the proposed method has less overall latency than other related methods. The proposed method has lower latency than the previous methods due to the selection of optimal nodes based on multiple objective functions in each step of packet transmission.

5. Discussion and Conclusion

As mentioned, this paper presents a reliable routing approach for IoT healthcare applications. Healthcare systems are trying to send data safely through highly reliable routes on the network. Therefore, this paper tries to achieve this goal by presenting an approach based on a multiobjective genetic algorithm. The main innovation of this paper is the integration of important goals of the network in the fitness function, which tries to find the optimal path by creating a tradeoff between these goals. According to the findings in experiments and by the implementation of the

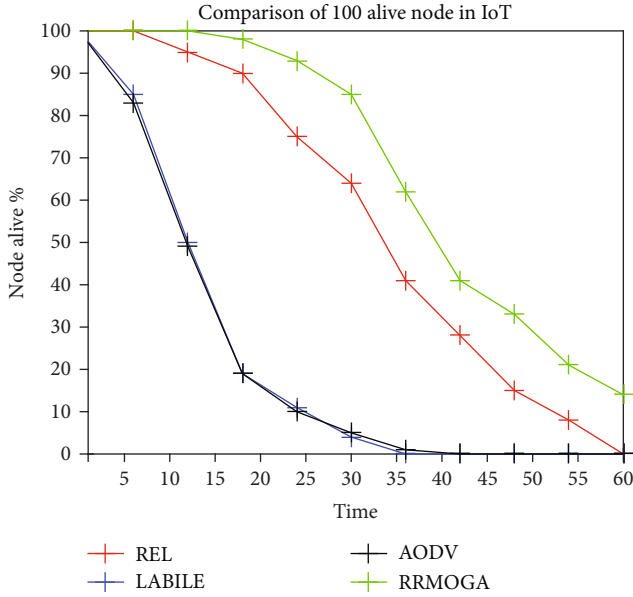


FIGURE 16: Comparison between the proposed method and previous methods in the aspect of live nodes.

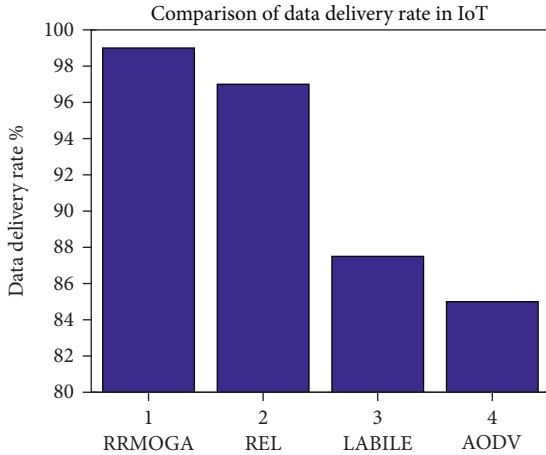


FIGURE 17: Comparison between the proposed method and previous methods in terms of the data delivery rate.

Internet of things, it can be seen that the method proposed in this article has not sacrificed other goals for reliability. The present method tries to improve reliability along with other objectives such as throughput, data delivery rate, network lifetime, and delay. The multiobjective fitness function used in the proposed method has created a tradeoff in the mentioned parameters. Previous methods have focused on one of the goals in the network, and therefore, optimal local routes have been found in each method and other basic parameters in the network have been ignored. For this reason, the proposed method not only has increased reliability but also has improved other basic network parameters. Findings show that the proposed method has been able to achieve better results compared with previous methods by relying on the multiobjective fitness function.

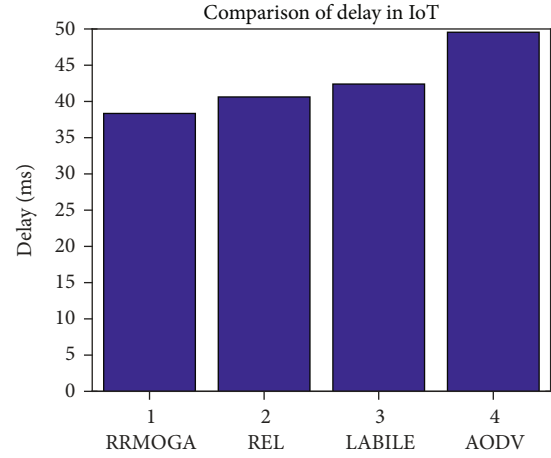


FIGURE 18: Comparison between the proposed method and previous methods in terms of data transfer delay.

In this paper, we have used reliable agents to send packets. Therefore, in each step, the proposed method selects an optimal reliable route and an alternative reliable route for sending packets. Both routes are composed of optimal agents. If data transmission is difficult in the near-optimal initial reliable agents, the proposed method uses an alternative route for sending data packets. Therefore, the data delivery rate in the proposed method is high, which the results of experiments and simulations prove the claim.

In this research, the secure routing protocol in IoT networks in the healthcare context is presented based on a multiobjective method as well as a multiobjective genetic algorithm. In the proposed method, chromosomes are selected as paths between the source node and the base station. Their proportionality function is considered based on network factors including distance between nodes, the base station, link quality, and degree of reliability. The proposed method, in each step, considers the optimal path and optimal nodes in order to transfer data in the network. Each node is considered as a factor of IoT-connected equipment in the IoT network in the healthcare context. The path between the source node and the base station is identified as an interconnected set of agents. Support factors are also selected as backup pathways, including the second optimal chromosome in the multiobjective genetic algorithm, to increase reliability. The simulation results of the proposed method show that the proposed method, in addition to having a longer network life and data delivery rate compared with other previous methods, has also reduced the data transmission delay. The proposed method, via using the balance between objectives in the proportionality function, is able to provide a secure approach to information transfer with minimum latency. Therefore, by balancing several objectives in network routing, the proposed method has been able to achieve good results in comparison to previous methods. The simulation results show that the proposed method, due to the use of reliable agents, has achieved reliability and data delivery rates, 99% and 99.9%, respectively, which have significantly improved compared to previous methods.

Data Availability

The data used to support the findings of this study have been adjusted according to standard setting and the results have been extracted from simulation.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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