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Network energy optimization and intelligent routing in WSN applicable for IoT using self-adaptive coyote optimization algorithm

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Summary

The Internet of Things (IoT) is a recent wireless telecommunications platform, which contains a set of sensor nodes linked by wireless sensor networks (WSNs). These approaches split the sensor nodes into clusters, in which each cluster consists of an exclusive cluster head (CH) node. The major scope of this task is to introduce a novel CH selection in WSN applicable to IoT using the self-adaptive meta-heuristic algorithm. This paper aids in providing the optimal routing in the network based on direct node (DN) selection, CH selection, and clone cluster head (CCH) selection. DNs are located near the base station, and it is chosen to avoid the load of CH. The adoption of the novel self-adaptive coyote optimization algorithm (SA-COA) is used for the DN selection and CCH selection. When the nodes are assigned in the network, DN and CCH selection is performed by the proposed SA-COA. Then, the computation of residual energy helps to select the CH, by correlating with the threshold energy. CCH is proposed to copy the data from the CH to avoid the loss of data in transmitting. By forming the CCH, the next CH can be easily elected with the optimal CCH using SA-COA. From the simulation findings, the best value of the designed SA-COA-LEACH model is secured at 1.14%, 3.17%, 1.18%, and 7.33% progressed than self-adaptive whale optimization algorithm (SAWOA), cyclic rider optimization algorithm (C-ROA), krill herd algorithm (KHA), and COA while taking several nodes 50. The proposed routing of sensor networks specifies better performance than the existing methods.

KEYWORDS

clone, intelligent routing, Internet of Things, multi-objective routing, network energy optimization, self-adaptive coyote optimization algorithm, wireless sensor networks

1 | INTRODUCTION

Modern wireless communication networks gains huge significance in recent days, among them Internet of Things (IoT) is the most recent and required communication networking field. Similarly, wireless sensor network (WSN) technology is also a major part of networking, which is mostly dependent on the set of sensor nodes correlated with wireless media, and IoT is fully relied on WSNs.[1] It is a famous field in the emergence of technologies possessing noteworthy possibilities in the cloud-based IoT. However, there are several research problems, which have to be solved for efficient operation and also attain the features of WSN technology.[2] The real-life solutions are developed in recent decades with the current progressions in wireless communication mechanisms for prolonging the lifespan of WSNs. In addition, the lifetimes of these networks suffer from several challenges like limited power supply, poor communication bandwidth, and low memory size.[3,4] Moreover, it is complicated to recharge or replace the batteries of employed sensors due to the hostile nature of the sensing atmosphere. Thus, the main complication in the implementation of WSN is how to decrease the energy utilization for extending the lifespan of the network.

Nowadays, several approaches have been designed for saving energy consumption, where multi-objective intelligent evolutionary computational methods are an alternative option for the abovementioned purposes.[5] These approaches aim to offer a possible set of solutions and resulted in getting the minimum and necessary rate of energy consumption. In WSN, the design of sensor nodes is taken as less mobile, where every node must have a similar initial energy level, which can make their own decisions locally, and the nodes pertaining to that cluster will be connected in one hop along with the cluster head (CH).[6] By considering all these conditions, the sum of the energy employed for both reception and transmission is defined as the energy consumption made by a sensor node. Thus, to enlarge the network lifespan and manage network energy utilization, the clustering technique is one of the most efficient approaches. Here, the clustering-based hierarchical methods partition the entire sensor nodes into groups called clusters, where the leader node is elected from each cluster, which is known as a CH, and the residual nodes are indicated as cluster members. The CHs are responsible to gather complete sensed data from cluster members and forwarding them to the base station (BS).[7,8] Additionally, one of the necessary tasks in the hierarchical clustering technique is the CH node selection process, which has concentrated on enlarging the stability of the network, throughput, lifetime, and energy consumption. In recent studies, most of the researchers focus on reducing energy consumption and extending the lifetime of the network by implementing the meta-heuristic-based clustering approaches because of the strong challenges of the clustering problem in WSN.[9] A contemporary and important goal of WSNs is energy efficiency. This aim is considered in several studies that have improved the network performance regarding latency, throughput, packet error rate, transmission cost, load balancing, and energy consumption. Through altering some of the advantages of these technologies, several researchers have proposed various schemes for improving the energy saving of the sensor node.[10,11]

Some of the clustering algorithms designed are the multi-objective fractional lion (FLION) clustering algorithm and the FLION clustering algorithm to get energy-efficient routing paths with optimization. They have focused on extending the lifetime of the network nodes and increasing the energy of the network by choosing the rapid CH, where during transmission, this model has lost energy.[12,13] Moreover, the optimization of CH selection is carried out through “Fractional calculus and Artificial Bee Colony (FABC) algorithm” for increasing the network lifespan and offering the maximum energy in the network, where the major complication is to transmit the data from on sensor node to other sensor nodes. The hybridization of the particle swarm optimization (PSO) algorithm and the harmony search algorithm (HSA) is adopted to select the energy-efficient CHs.[14,15] Moreover, this approach further minimizes data communications as there is no change or little change in the sensed attribute.[16,17] It is utilized to resolve constraint optimization problems, and also, it is applicable for real-world applications. These techniques motivate to concentrate on developing a novel heuristic algorithm for energy-efficient routing in WSNs.

The major contribution of the designed model is discussed here.

- To suggest a new network energy optimization and offer a heuristic-based effective routing in WSN for IoT intending to enlarge the energy utilizations and enlarge the network lifespan.
- To select the direct nodes with the help of SA-COA and choose the CHs in each cluster of the entire sensor network by assigning threshold levels for residual energy to minimize the mean energy and distance among sensor nodes.
- To choose the clone cluster head (CCH) using SA-COA for avoiding data loss and assist the CHs in every cluster by resolving the fitness function regarding degradation of Euclidean distance, minimization of delay, maximization of throughput, maximization of balance energy, and maximization of the lifetime of the network.
- To evaluate the efficiency of WSN in IoT with several constraints by comparing with several optimization algorithms to enlarge the performance of network energy optimization.

The remaining sections of the designed model are given here. Section 2 analyzes the baseline approaches. Section 3 develops a new routing model in WSN and IoT using CH selection and CCH selection. Section 4 presents a self-adaptive coyote optimization algorithm (SA-COA) for optimal routing in WSN and IoT with the selection of direct node and CH. Section 5 introduces the optimal CCH selection using a new multi-objective function. Section 6 shows the result visualization. Section 7 completes the given task.

2 | LITERATURE SURVEY

2.1 | Related works

In 2014, Park et al.[18] planned an "Energy-Efficient Probabilistic Routing (EEPR)" approach for minimizing packet loss and maximizing the network lifetime by controlling the transmission of routing request packets in a stochastic way. By utilizing the expected transmission count (ETX) measure and residual energy of each node, the energy-efficient probabilistic control was adopted into the designed method. With the help of the simulation study, it was confirmed that the designed approach has taken the remaining energy of each node more evenly and attained a longer lifetime of the network when compared with the conventional "Ad-hoc On-demand Distance Vector (AODV) protocol."

In 2017, Sun et al.[19] presented a novel routing technique through ant colony optimization (ACO) algorithm through finding the optimal path, residual energy, transmission direction, and node communication transmission distance, which has also enhanced the heuristic function. Hence, the network lifetime has also been extended, and the network energy consumption was reduced. The experimental outcomes have observed that the new ACO algorithm has considerably extended the network lifespan and saved the energy of nodes.

In 2017, Lee et al.[20] developed an enhanced low-energy adaptive clustering hierarchy protocol for mobile sensor networks (MSNs). It has been utilized to extend the network lifetime and also decrease packet loss using fuzzy inference systems. Here, the simulation results have revealed that the afforded method has more efficient than the other conventional techniques regarding diverse metrics.

In 2017, Alami et al.[21] introduced a new routing protocol regarding smart energy management and throughput maximization for clustered WSNs. The major scope of this protocol has to resolve the parameter of the closest sensors to the BS and also reduce the workload on CHs. In the end, the simulation findings have shown that the offered method achieves more efficient performance than the other protocols.

In 2018, Mayee et al.[22] changed the conventional LEACH clustering protocol by adopting threshold limits for selecting the CHs with simultaneous switching of power levels among the nodes. The designed altered LEACH clustering protocol was shown the superior efficiency while testing with baseline protocols regarding the count of alive nodes and throughput that has aimed for enlarging the network lifetime, which has outperformed the existing approaches regarding network lifetime and stability period in diverse circumstances of node density, energy, and area.

In 2018, Alami et al.[23] implemented a new strategy of a clustering algorithm for decreasing the data communication distance in WSNs. Additionally, hierarchical routing protocols were adopted for heterogeneous and homogeneous networks. At last, the findings have shown that the offered strategy is more effective than other existing protocols.

In 2019, Mostafaei[24] designed a "Distributed Learning Automaton (DLA) algorithm" for preserving the network characteristics in terms of "Quality of service (QoS) routing" in WSNs, particularly for surveillance systems. Owing to the high energy efficiency and packet loss, multi-hop data transmission of WSNs has needed reliable links for delivering the data in an end-to-end manner. The recent multipath routing approaches have ensured the QoS requirements in terms of delay and end-to-end reliability, which may suffer from a considerable energy cost. For preserving the preferred QoS requirements, the designed DLA was assisted to discover the smallest number of nodes in the network. The simulation of the proposed algorithm has established the efficiency of the solution, in which the outcomes have demonstrated that the designed approach has shown superior efficiency to existing competitive algorithms.

In 2019, Wang et al.[25] developed an improved energy optimization routing protocol for selecting double CHs in clustering WSNs, which was computed through the energy welfare function. The energy overhead was presented by a formula for balancing nodes' energy. Further, the relay nodes have communicated the sensory information to the sink during the routing selection by integrating multi-hop and single-hop technology. The relay node selection was carried out based on the weight values concerning the distance between two nodes, the number of selected times as relay nodes, the number of nodes in the cluster, and residual energy. The experimentation was conducted on the designed protocol, which has shown a competitive performance than other existing protocols owing to prolonging the network lifetime and maximizing the energy utilization efficiency.

In 2020, Mohamed et al.[26] implemented a "Coyote Optimization based on a Fuzzy Logic (COFL) algorithm" for suggesting a novel clustering framework for heterogeneous WSN, which has balanced and reinforced the clustering procedure with the aim of "maximizing the network lifetime and minimizing the energy consumption." They have also determined the possible set of CHs through the COFL technique. Moreover, a new fitness function has been introduced for minimizing the "total intra-cluster distance among every CH node and its cluster members that have also minimized the inter-cluster distance among the CHs nodes and the base station." The designed COFL algorithm has shown a competitive performance over other existing algorithms in terms of vital tendency measurements for normalized energy, alive nodes and throughput, energy consumption, and alive node analysis.

In 2020, Govindaraj and Deepa[27] examined an efficient network energy optimization for IoT sensor nodes regarding WSNs. Here, superior performance was achieved by proposing the "capsule neural network architectural model" by reducing the network energy overhead for WSN-derived IoT. In WSNs, every sensor node has transmitted in a different way to transfer the information from the IoT cloud to the virtual modules. In general, the clustering in the sensor has focused on enhancing the accuracy rate. The highly complex clustering approaches have aimed for getting a high accuracy rate and managing the energy in optimizing the IoT in WSNs. Simulation results of the suggested neural network framework have attained the effectiveness and reliability for energy optimization of IoTs in WSN by comparing with the conventional approaches.

In 2021, Chowdhury and De[28] introduced a "Voronoi-Glowworm Swarm Optimization-K-means algorithm (VGSO-KA)" for designing an energy-efficient coverage optimization approach for enhancing the coverage field with a lesser number of alive nodes. This model has determined the optimum sensing radius for the effective deployment of sensor nodes. Additionally, the designed model using the sleep–wake mechanism and the multi-hop transmission has aimed to improve the lifetime of the employed network by reducing the consumed energy by the employed sensor nodes. The simulation results have shown that 99.99% of the area coverage was attained by the designed model with the optimum number of active sensor nodes.

2.2 | Problem statement

In WSN, a challenging research area is expanding the lifespan of the network through the optimization of network energy expenditure. It is very difficult to determine the way for generating effective data routing mainly in the energy-

TABLE 1 Upperhands and downsides of existing network energy optimization model.

Author [citation]	Techniques	Upperhands	Downsides
Park et al.[18]	EEPR	• It is composed of a longer lifespan of the system and evenly intakes the residual energy for all the nodes.	• On the other hand, the probability of routing success rate gets reduced.
Mostafaei[24]	RRDLA	• It attains a stable balance between the diverse QoS constraints like energy utilization and end-to-end delay.	• Yet, the average delay is reached to be higher when the count of nodes gets enlarged in the network.
Mayee et al.[22]	I-LEACH protocol	• It acquires an extended network lifespan with reduced energy utilization in a distributed manner.	• It does not consider the heterogeneous routing protocols for determining results.
Mohamed et al.[26]	COFL	• It provides significant performance regarding the central tendency measurements for the normalized energy, throughput, energy consumption, and alive node analysis.	• However, it fails to satisfy the network configuration for solving the mobile nodes as the BS or sensor nodes.
Sun et al.[19]	ACA	• It reduces the utilization of average energy and prolongs the lifespan of the WSN.	• It affects the network energy consumption.
Chowdhury and De[28]	VGSO-KA	• It has enhanced the coverage area with a "minimum number of active nodes."	• It is essential to mention the count of clusters in advance. • It is difficult to handle noisy data and outliers.
Govindaraj and Deepa[27]	CNN	• It improves the network quantity by managing the energy utilization rate and enhancing the data accuracy rate.	• It lacks stability of the training progress and leads to global minima, which further maximizes the computational time.
Wang et al.[25]	PARPEW	• It does not overload the data fusion and data forwarding.	• However, the cluster head energy at the BS gets reduced owing to the overhead of the transmitting data.

constrained WSNs. Various approaches have been developed for optimizing the network energy in the WSNs that are depicted in Table 1.

- EEPR[18] is composed of a long lifetime of the network and evenly intakes the residual energy for all the nodes. On the other hand, the routing setup delay gets enlarged and the probability of routing success rate gets reduced. The brief discussion based on the node delay and also the probability of routing success rate gets will be considered as upcoming work.
- RRDLA[24] attains a stable balance between the diverse QoS constraints like energy consumption and end-to-end delay, yet the average delay is reached to be higher when the count of nodes gets bigger in the network. The brief discussion based on the node delay will be taken as future work.
- I-LEACH protocol[22] acquires an extended network lifetime with reduced energy consumption in a distributed manner, yet it does not consider the heterogeneous routing protocols for determining results. In the given present work, the heterogeneous routing protocols will be included for determining the results.
- COFL[26] provides significant performance regarding the central tendency measurements for the normalized energy, throughput, energy consumption, and alive node analysis. However, it fails to satisfy the network configuration for solving the mobile nodes as the BS or sensor nodes. The given present work provides the guarantee to assure the network design for resolving the mobile nodes as the BS or sensor nodes.
- ACA[19] reduces the consumption of average energy and prolongs the lifetime of the WSN, but it affects the network energy consumption. The simulation findings of the given present work have minimized the network energy consumption.
- VGSO-KA[28] has enhanced the coverage area with a minimum number of active nodes, but it is essential to mention the count of clusters in advance, and also, it is difficult to handle noisy data and outliers. The investigation of noisy data and outliers issues will be considered an upcoming work.
- CNN[27] improves the network quality by managing the energy consumption rate and enhancing the data accuracy rate. On the other hand, it lacks the stability of the training progress and leads to global minima, which further maximizes the computational time. The simulation findings of the given present work minimize the computation time.
- PARPEW[25] does not overload the data fusion and data forwarding and also avoids the premature death of the CH nodes. However, the CH energy at the BS gets reduced owing to the overhead of the transmitting data. The maximization of CH energy at the BS will be taken as future work.

Therefore, to overcome these above existing challenges in energy optimization in WSNs, it is necessary to implement a new energy optimization protocol for WSNs.

3 | NOVEL ROUTING MODEL IN WSN AND IOT USING CH SELECTION AND CCH SELECTION

3.1 | Routing in WSN and IoT

IoT is a network that ensures novel ways of communication among different devices. Every node or object or thing in an IoT network plays a major role and also aims on communicating with others. In IoT with the future network, every node gathers the information itself, and that information is verified by humans. IoT is emerging in various areas like smart environments, healthcare, and transportation, where the major network systems to communicate with things in IoT are WSN, "Radio-Frequency Identification (RFID) systems," and RFID sensor network (RSN).[29] These network types for IoT distribute the nodes in a precise area for an exacting purpose and collect the necessary information, where the node collects the information regarding physical changes, motion, temperature, energy, and so on. The collected information is forwarded to the intermediate nodes due to the restricted transmission bound of the node. Thus, the intermediate nodes utilize the unplanned energy for forwarding the packets from the source node which creates huge consumption of energy, and then, the network portioning will be accelerated. Moreover, the major element that influences the network efficiency in distributed networks for IoT is the "energy efficiency of the nodes."[30] Further, in the IoT network framework, nodes are often taken as sensors with more restricted in their resources like energy battery powered, communication range, computational power, and memory. In addition, sensor nodes are often randomly taken in a distributed way with autonomous configuration and different densities along with communication network protocol.[31]

IoT network is developed dependent on the necessary application, which considers the major element as the sensor with restricted resources along with BSs, gateways, and rechargeable nodes, which needs to stream the gathered data into the Internet.[32] For evaluating the efficiency of the network, routing protocols are used in the IoT topology scenario along with the randomly partitioned nodes. However, this case does not offer a possibility of utilizing the energy of nodes, particularly for IoT applications, which has some types of various level of energy heterogeneity nodes like mobile, phones, sensors, and passive RFID. Thus, there is a need of proposing a practical IoT architecture, which offers network division into regions by taking the major energy level in every domain.[33] As an example, random distribution of nodes is included in a heterogeneous region that is mostly consisted of some advanced nodes and normally limited energy nodes. The remaining regions consist of nodes with main-powered, rechargeable, higher contents of energy, and so on. IoT exists at a higher level than WSN, and WSN is an eminent technology utilized within an IoT system. It includes a huge set of sensor nodes or sensor devices installed with the major objective as the sensed information in their monitoring region based on the application necessities like security monitoring, wildlife, and health.[34] In such applications, sensor nodes are implemented with the ability to sense several categories of data like temperature, light level, or other environmental data, which may execute data aggregation after transmitting the gathered data to the BS. In addition, the data processing and forwarding are based on the objective considered in the environment. On the other hand, routing designs in WSN have to deal with several limitations like tradeoffs among efficiency and responsiveness. Similarly, while designing the WSN, some of the constraints like the type of application, data aggregation, scalability, energy consumption, and node deployment must be considered.[35] The major issue in the sensor network is the restricted energy due to the non-rechargeable battery and limited energy source of sensors, where the appropriate design must extend the lifetime of the sensor network. Therefore, the design of an effective routing technique may considerably minimize the energy consumption of WSNs.[36] In literature, several routing algorithms are presented, where the hierarchical or CH-based routing protocols are taken as one of the eminent protocols for energy-efficient WSNs. The major concept of a hierarchical protocol is to separate nodes into various clusters, where every group must have CHs for coordinating with their members in every cluster.[37] As sensor nodes are generally powered by batteries, they may exhaust some time and so, the network may not work appropriately. Thus, energy saving has been considered a major role in the energy operation of WSNs. Conventional approaches focus on extending the overall "lifetime of the network, reducing the energy consumption of the path" and also minimizing the transmission distance. The nodes often transmit data to the BS via multi-hops because of the restricted communication among sensor nodes. The major concern for routing techniques is to discover the path with minimum energy consumption from the source node to a BS.[38] Hence, these nodes must consider the limitations like memory, communication range, and energy consumption; however, energy consumption is the major complication in WSN. Thus, the primary objective of designing WSNs is to efficiently use of node's energy. Hence, this paper introduces the network energy optimization in WSN for IoT with the help of a heuristic algorithm. The architecture of "WSN for IoT applications" is given in Figure 1.

The network model considers some of the assumptions like entire nodes in the sensing region in a static manner. Then, equal energy is held by all the nodes in the networks. Based on the single hop, the sensor nodes will communicate their information. Then, CHs are selected in each cluster and then perform data aggregation by each CH, where CHs follow either multi-hop or single-hop communication. The energy model of WSN for IoT is given here.

The energy dissipation model[32] is considered to transmit $q-$ a bit packet to a distance d. Hence, the energy is being used as follows.

$$En_{TX}(q,d)=\begin{cases} qEn_{elec}+q\in_{fs}d^2, & d<d_{th} \\ qEn_{elec}+q\in_{mp}d^4, & d\geq d_{th} \end{cases} \tag{1}$$

The parameter for multipath model is given as $\in_{mp}$, the threshold distance is indicated as $d_{th}=\left(\sqrt{\frac{\in_{fs}}{\in_{mp}}}\right)$, the energy parameter for free-space mode is termed as $\in_{fs}$, the distance among the receiver and transmitter is derived as d, the energy parameter regarding the "energy consumption during transmission or reception of 1-bit" is noted as En_{elec}, and the packet size is denoted as q. The energy consumption to receive $q-$ a bit packet is formulated in Equation (2).

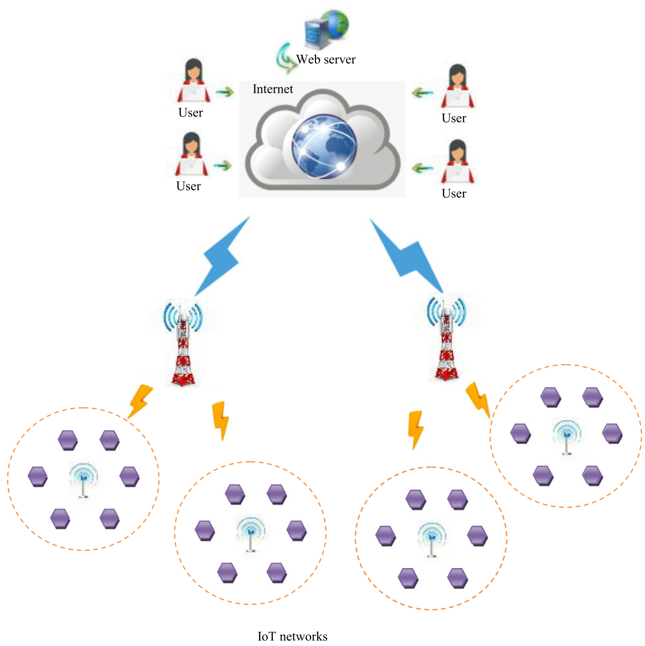

FIGURE 1 The network architecture of Internet of Things (IoT).

$$En_{RX}(q) = qEn_{elec} \tag{2}$$

3.2 | Proposed architecture

WSNs and IoT are the major force of technology in the recent world. IoT integrates several devices that help in communicating each aspect of life. WSNs disclose their ability every day in each aspect of life. Thus, a combination of IoT and WSN upgrades the utilization of the application to the next level and makes life easier. It helps in reaching various applications. However, merging these technologies requires cautious consideration about getting both on a similar level. IoT is taken as a powerful monster with numerous abilities and power. However, WSNs are small networks with restricted resources and huge abilities for penetrating most aspects of life. While combining the IoT with WSNs, there is a need of considering the limited resources.[39] This integration also helps in exploring access to the world by sensor devices, which also creates complications. Additionally, the addressing and topology of WSNs are diverse from the normal internet, which requires to be solved while performing the integrations. Routing is an approach for creating the route among source and destination nodes. Moreover, routing protocols consider the objectives as the shortest path communication, which brings several conditions like best QoS, less delay, and energy consumption for enlarging the network lifetime through saving energy and increasing the number of alive nodes. The major challenge in IoT is to handle the huge range of deployed sensors regarding the cost of maintenance and servicing.[8] Moreover, replacing the batteries of sensor nodes that are previously positioned in the network area can be a complicated issue. Similarly, while placing the sensor devices in real-time applications, battery replacement plays a major role, especially in wildlife applications. Hence, power management in IoT networks is a tedious job. In addition, WSN has to solve some problems like lower packet loss ratio and necessary congestion control with reliable end-to-end data transmission. IoT with WSN application suffers from various limitations regarding computational cost, battery power, mode of communication, hardware, several sensor nodes, and so on.[40]

The sensors utilized in IoT network have to consider some additional functionality and handle power management and QoS issues, which can be solved through different technological variations in primitive protocols and strategies utilized for WSN. IoT-based WSN includes some QoS requirements, which suffer from issues such as multiple sink nodes or BSs, heterogeneous network, less reliable medium, dynamic size of the network, redundancy in data, and extreme resource content. WSN also faces some security problems like freshness in data, data integrity, confidentiality, and data authenticity. While developing WSNs, the minimization of power consumption has already been a complicated problem. Although recent tasks have concentrated on extending the network lifetime and reducing the energy with the suitable usage of resources, it further requires additional services for improving the network performance. In IoT-derived WSN, clustering schemes construct a group of sensing nodes or a hierarchy of clusters to collect and transfer the data to their corresponding CH.[41] Further, it is forwarded to the BS by CH. However, if CH fails in transmission, then the network faces some complications. Hence, this paper suggests a new scheme for designing an IoT-WSN network, which is diagrammatically represented in Figure 2.

The main scope of the offered model is to perform the direct node selection, CH selection, and CCH selection in WSN for IoT with the aid of the SA-COA technique. At first, the network with several counts of sensor nodes is assigned in WSN for IoT. Further, the nodes are partitioned into clusters for routing in WSN. The main scope of the designed model is to offer optimal routing with three objectives, where initially, the direct nodes are selected in the clusters with the help of SA-COA. Then, the CHs are selected regarding the threshold with the remaining energy, where the remaining energy is computed for selecting the CHs by correlating with the threshold value. The major scope of the designed network is to reduce the Euclidean distance and mean energy of the network. Then, SA-COA helps in selecting the CCH for avoiding the loss of data during transmission if CH fails in clusters. Further, through the selected CCH, a new CH will be selected with the next optimal values with the residual energy-derived threshold value. Here, the multi-objective function is formulated for CCH selection with constraints like delay, throughput, residual energy, and a lifetime of the network. Thus, it finally ensures the optimal routing in WSN for IoT with the aim of network longevity and higher network performance.

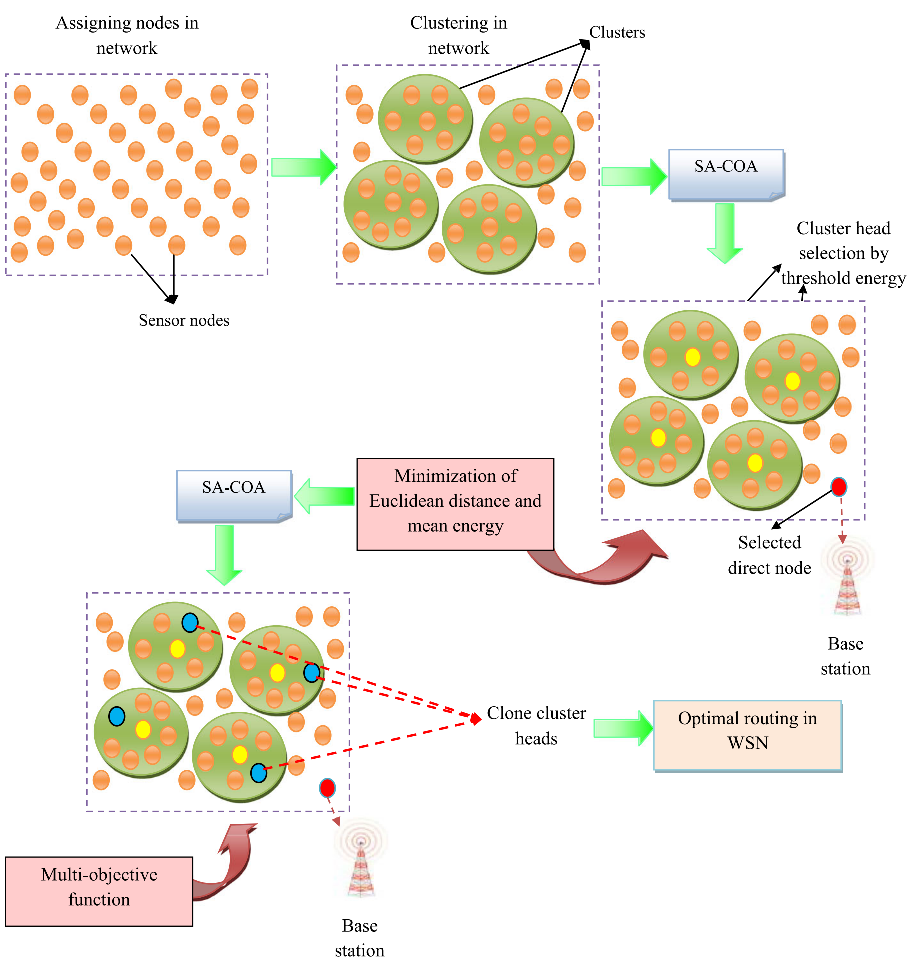

FIGURE 2 Network energy optimization and intelligent routing in wireless sensor network (WSN) applicable for Internet of Things (IoT).

3.3 | CH selection versus CCH selection

Clustering is an eminent technique to enlarge the network lifetime in WSNs. It consists of several number sensor nodes, which are grouped into clusters, and then, CH is selected in each cluster. One of the major concepts in routing in WSN is to select the CH for balancing the load in the network, which aims to increase the network lifetime and minimize energy consumption.[42] CHs are in charge of collecting the data from the sensor nodes in the clusters and then forwarding the collection of data to the BS. However, the major issue in WSNs is choosing suitable CHs. Moreover, the CH must be in an active state when the member nodes can go to rest mode at time intervals. Hence, more energy consumption is observed by each CH, and thus, it can be dead after some time intervals. Hence, an alternative solution is required. Some CHs drain their energy and so, the lifetime of the network is reduced. Moreover, CH selection has several limitations as given here. CH node may rapidly fail while ignoring the geographic location, residual energy, and other information. Moreover, they do not consider the location of nodes. Once the CH was dead, the cluster member nodes deplete energy.[43] While different nodes have separate energy levels, the unreasonable CH selection is noticed. At a similar time, different clusters may vary in terms of size, and thus, CH selection must be reasonable.[44]

Thus, a new CCH selection is introduced in existing studies. It is used for replacing the CH during transmission. Moreover, CCH helps to avoid data loss and also increases the network lifetime. The difference between CH and CCH is given in Figure 3.

4 | SA-COA FOR OPTIMAL ROUTING IN WSN AND IOT: SELECTION OF DIRECT NODE AND CH

4.1 | Proposed SA-COA

A new SA-COA is implemented in this paper for optimizing the network energy in WSN[45,46] for IoT applications, where the SA-COA is used for selecting the direct nodes, and CCH. This helps in extending the network lifetime and performance of the network. COA attains better solutions when compared with other conventional algorithms.[47,48] COA[47] gives several advantages like offering global optimal solutions and effective balancing among exploration and exploitation phases because of its unique algorithmic structural setup. The performance is enhanced as it uses only two parameters like count of packs and the number of coyotes per pack. This algorithm suffers from premature convergence and falls into local optimal. Thus, there is a need of adopting a new optimization algorithm with the help of the self-adaptive nature concept. The SA-COA is implemented by altering the random parameter rn_j with the help of fitness-based solutions of recent and previous iterations, whereas, in the existing COA, this rn_j lies among [0, 1]. In SA-COA, rn_j is modified as given in Equation (3).

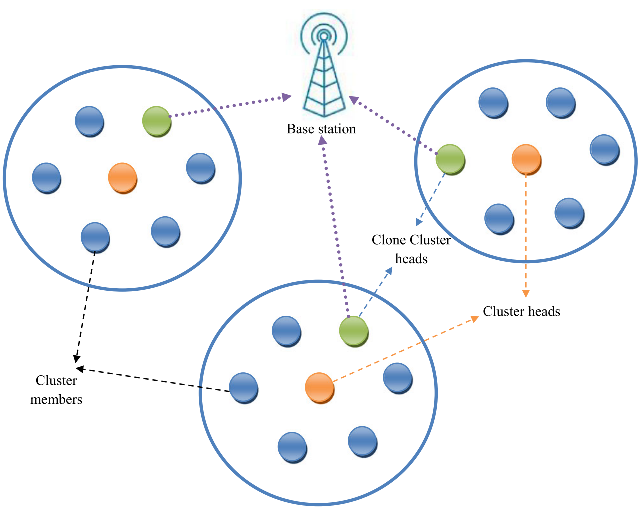

FIGURE 3 Cluster head and clone cluster head in Internet of Things (IoT) network.

$$rn_j = abs\left(\frac{Fn(j-1) - Fn(j)}{Fn(j-1)}\right) \tag{3}$$

COA[8] is one of the famous population-based swarm intelligence techniques. It is founded on the swarm characteristics of coyotes (solution). Initially, the location of the solution is arbitrarily set as Equation (4).

$$Y_j = lb_j + rn_j \times \left(ub_j - lb_j\right) \tag{4}$$

The count of solutions per pack is restricted to 14 in COA for giving the better exploration capability of the algorithm. The best coyote is chosen based on a better solution adapted to the platform with the lower cost function attained from the minimization problem and vice versa. The lower bound and upper bound of the candidate are denoted as lb_j and ub_j, and the position of a coyote at j^{th} dimension is denoted as Y_j. To maintain the packs, the organization of coyotes is done for distributing the social conditions. In addition, the social tendency of the pack is determined in Equation (5).

$$X_j^{g,h} = \begin{cases} S^{g,h}_{\frac{(Np_s+1)}{2}}, & Np_s\, is\, odd \\ \dfrac{S^{g,h}_{\left(\frac{Np_s}{2}+1\right),j}}{2} & or\ else \end{cases} \tag{5}$$

Here, the term $X_j^{g,h}$ indicates the social tendency of the involved coyote in g^{th} the pack at a time h in the range of [1, DS], the ranked criteria of coyotes are represented by S, and the count of coyotes is denoted as Np_s. Further, in Equation (6), the determination of the birth of a new coyote by considering the birth and death of coyotes is derived from Equation (6).

$$Bi_j^{g,h} = \begin{cases} Y^{g,h}_{rm1,j}, & rn_j \geq \rho_{sp} + \rho_{ap} or j = j_1 \\ Y^{g,j}_{rn2,j}, & rn_j < \rho_{sp} or j = j_2 \\ RN_j, & otherwise \end{cases} \tag{6}$$

In Equation (6), the term ρ_{ap} is defined as the scattering probability given by and ρ_{sp}, which are measured in Equations (8) and (7); the two coyotes are randomly chosen from g^{th} the pack, which are expressed by $rn1$ and $rn2$.

$$\rho_{sp} = \frac{1}{DS} \tag{7}$$

$$\rho_{ap} = \frac{\left(1 - \rho_{sp}\right)}{2} \tag{8}$$

The social situation of each S^{th} coyote in the g^{th} pack is upgraded at the every iteration as shown in Equation (9).

$$Y_s^{g,h+1} = \begin{cases} Y_s^{g,h} + rn1 \times \sigma_1 + rn2 \times \sigma_2, & Fn_s^{g,h+1} < Fn_s^{g,h} \\ Y_s^{g,h} & or\ else \end{cases} \tag{9}$$

Additionally, the alpha effect and the pack effect formulated as σ_1 and σ_2 are derived in Equations (10) and (11).

$$\sigma_1 = alpha^{g,h} - Y^{g,h}_{rn1} \tag{10}$$

$$\sigma_2 = X^{g,h} - Y^{g,h}_{rn2} \tag{11}$$

In the aforementioned equations, the alpha coyote is termed as $alpha^{g,h}$ and the social condition cost is denoted as $Fn_S^{g,h+1}$.

$$Fn_S^{g,h+1} = fn\left(Y_S^{g,h}\right) \tag{12}$$

At last, the best coyote is attained with the best solution obtained for the problem. Self-improvement in this paper offers a better convergence rate and reduces the premature convergence problem; thus, it increases the performance when compared with conventional optimization techniques.

Hence, this SA-COA increases the effectiveness by selecting the direct nodes and CCH in WSN for IoT. The pseudo-code of the SA-COA is Algorithm 1.

Algorithm 1 Proposed SA-COA

```
Initialize the Population
Set the fitness of each candidate
Compute the random number rn_j using Eq. (3)
Assume the accurate candidate as a food source
  While the stop condition is not met do
    for each coyote in the pack
      Determine the social tendency by Eq. (5)
      By, Eq. (9) the new condition is estimated
    End for
    Birth and death using Eq. (6)
  End while
Upgrade the population
Determine best solutions
end
Written best solutions
```

The flow diagram of the offered SA-COA is depicted in Figure 4.

4.2 | Direct node and CH selection

The selection of a direct node is the initial stage in the designed WSN for IoT. Direct nodes are located near the BS, and it is chosen for reducing the load of CH. This direct node selection is carried out using SA-COA for increasing the lifespan of the network, and thus, it maximizes the efficiency of the suggested model. The major objective of the direct node selection through SA-COA is done by considering the fitness function regarding the minimization of Euclidean distance among nodes and mean energy. The CH selection is also carried out through residual energy by correlating with the threshold value. The nodes that have the threshold value of 0.1 of residual energy are taken as the CH in each cluster, where the network lifetime can be extended along with the maximization of network efficiency. The selected CHs are denoted as CH_k, where $k = 1,2,3,\cdots,K$ and K indicates the average of CHs in the total number of clusters in the entire network,

The primary objective function of direct node selection and CH selection is formulated in Equation (13).

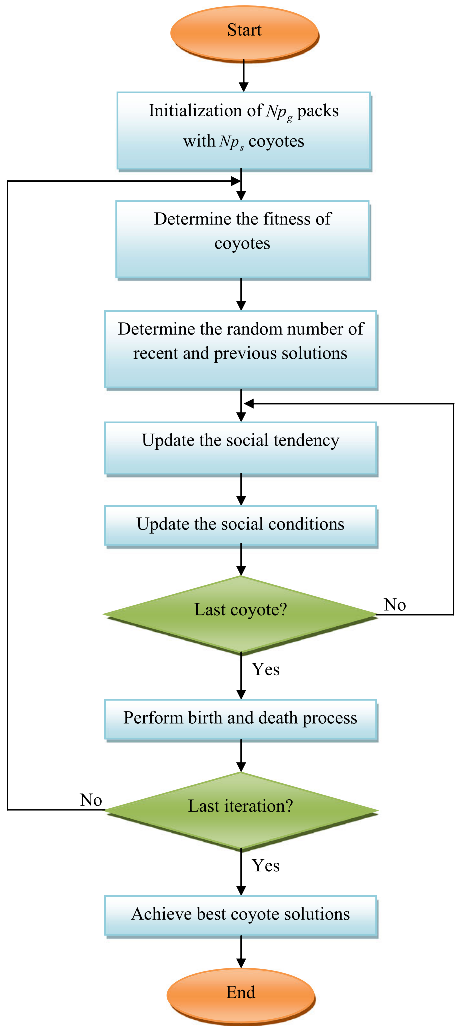

FIGURE 4 Flow diagram of the designed self-adaptive coyote optimization algorithm (SA-COA).

$$Fn_1 = \underset{\{Dn\}}{\arg\min}\,(Ed + En_{mean}) \tag{13}$$

Here, the number of direct nodes is termed as Dn, where the range of direct node selection is given from 1 to the average count of nodes in a sensor network. Term Ed specifies the Euclidean distance, and En_{mean} specifies the mean energy. Here, "Euclidean distance among two nodes" is defined as "the length of a line segment between the two nodes" as derived in Equation (14).

$$dis = \sqrt{(p_u - b_v) + (p_u - b_v)} \tag{14}$$

Here, the CHs taken for communication are defined as p and b, and the corresponding coordinates to these nodes are denoted as u and v. The distance between two IoT devices in the same cluster or other clusters is calculated for offering optimal routing. The mean energy En_{mean} of the entire sensor network at b^{th} round is derived in Equation (15).

$$En_{mean(b)} = \frac{1}{No} \times En_{total}\left(1 - \frac{b}{B_t}\right) \tag{15}$$

In Equation (15), the average count of nodes that existed in the network is denoted as No, the initial total energy of the network is indicated as En_{total}, and the average count of rounds is denoted as B_t. The selected direct nodes and CHs help in enlarging the network efficiency. The solution encoding of the direct node selection and CH selection using SA-COA is given in Figure 5. Here, the threshold level-based residual energy also helps in selecting the CHs.

5 | OPTIMAL CCH SELECTION USING NEW MULTI-OBJECTIVE FUNCTION

5.1 | Proposed CCH selection process

After selecting the direct nodes and CHs in every cluster, the CCH is selected using SA-COA for assisting the CHs. This CCH acts like CHs, which has the same characteristic and responsibilities as CH.

Each cluster is managed by both CH and CCH, where the major role of CCH is to save the network energy and it also saves time. Thus, CCH performs like CH in each cluster when the energy of CH is exhausted or when CH is dead. In this proposed model, CCH selection is carried out through SA-COA with the fitness function concerning Euclidean distance, delay, throughput, residual energy, and the lifetime of the network. The solution encoding of CCH using SA-COA is given in Figure 6.

The range of CCH selection is given as 1 to a total number of nodes in the sensor network, where the CCH is termed as CCH_k that is selected in each cluster in the sensor network.

5.2 | Explanation of fitness variables

The major objective function regarding minimization of Euclidean distance, minimization of delay, maximization of throughput, maximization of residual energy, and maximization of a lifetime of network for proposed CCH selection is given in Equation (16).

$$Fn_2 = \underset{\{CCH_l\}}{\arg\min}(f_4) \tag{16}$$

Here, the selected CCHs are given by CCH_l, and the fitness function is derived with the constraints like Euclidean distance, delay, throughput, residual energy, and lifetime of the network.

$$f_1 = (\alpha * dis) + [(1-\alpha) * De] \tag{17}$$

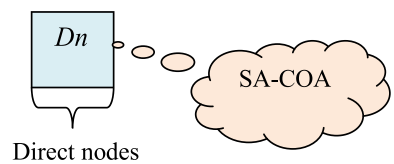

FIGURE 5 Solution encoding of the direct node selection using self-adaptive coyote optimization algorithm (SA-COA) in wireless sensor network (WSN) for Internet of Things (IoT).

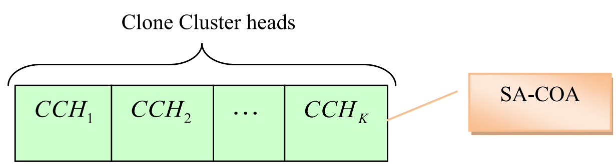

FIGURE 6 Solution encoding of clone cluster head (CCH) using self-adaptive coyote optimization algorithm (SA-COA).

TABLE 2 Simulation setup for the designed network energy optimization model in wireless sensor network (WSN) for Internet of Things (IoT).

Parameters	Values
Control packet size	200 bit
The initial energy of a node	0.5 J
Number of sensor nodes	200
Base station	(0, 0) meter
Data packet size	4000 bit
Network size	100*100 m^2
Number of node variation	[50, 100, 150, 200]
The energy parameter for the free-space model	10 pJ/bit/m^2
The average distance among all cluster heads and base station	85 m
The parameter for the multipath model	0:0013 pJ/bit/m^4
Maximum number of iterations	25
The threshold distance	88 m
"The energy parameter that says about the energy consumption during transmission or reception of 1-bit"	50 nJ/bit
Energy consumption for data aggregation	5 nJ/bit/signal
Number of population	10
Number of rounds	2000

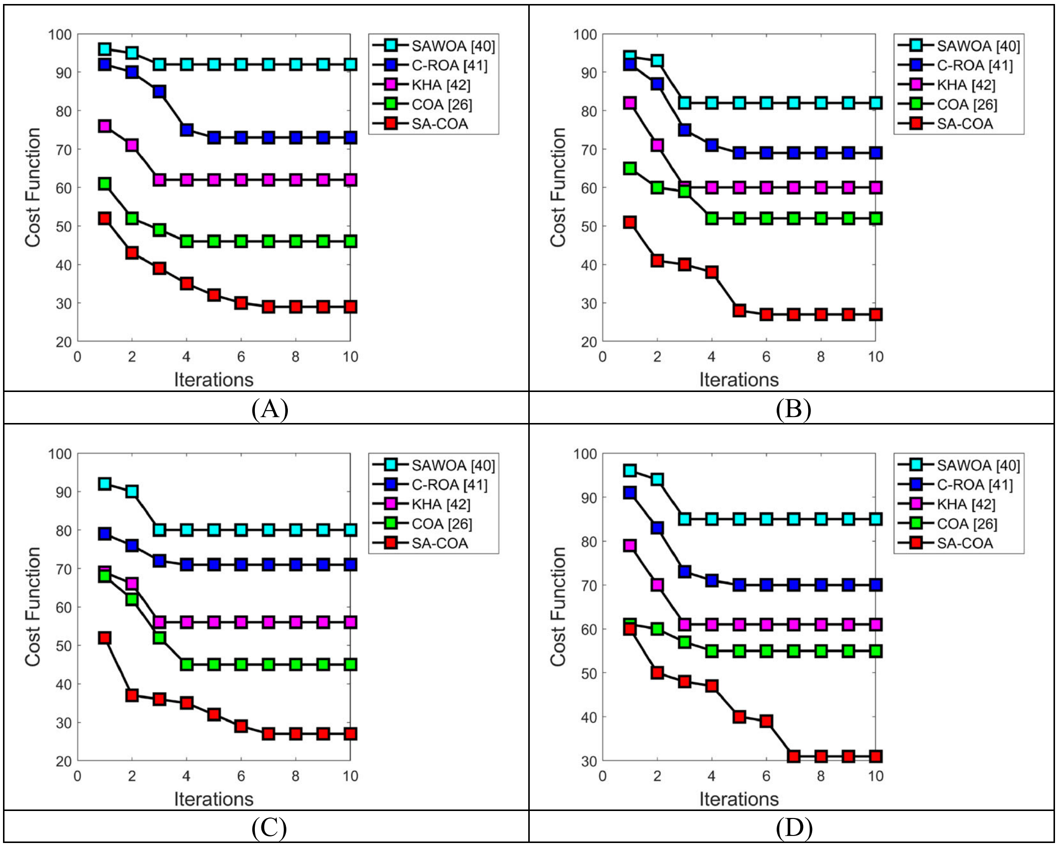

FIGURE 7 Convergence analysis of the designed network energy optimization and intelligent routing in wireless sensor network (WSN) applicable for Internet of Things (IoT) with the other optimization algorithms regarding differing the count of sensor nodes (A) 50, (B) 100, (C) 150, and (D) 200.

$$f_2 = (\beta * f_1) + \left[(1-\beta) * \frac{1}{Th}\right] \tag{18}$$

$$f_3 = (\gamma * f_2) + \left[(1-\gamma) * \frac{1}{En_{res}}\right] \tag{19}$$

$$f_4 = (\delta * f_3) + \left[(1-\delta) * \frac{1}{LN}\right] \tag{20}$$

In the aforementioned equation, Euclidean distance is termed as *dis* and it is formulated in Equation (21), where the values are assigned as $\alpha = 0.25, \beta = 0.25$, $\delta = 0.25$, and $\gamma = 0.25$. In addition, the delay is termed as *De*, where the "network efficiency can be increased while transmitting the data packets from source to destination node" in a restricted time. The latency time can be computed for transferring the packets from CH to BS, and *De* is measured in Equation (21).

$$De = \frac{\max \sum_{l=1}^{L} CCH_l}{No} \tag{21}$$

In Equation (21), the term *No* indicates the total nodes and the data transmission from CH to BS are derived as $\max \sum_{l=1}^{L} CCH_l$. Throughput is indicated as *Th* is derived as " the number of tasks completes the execution within a unit time." Throughput is based on the "execution time" of the tasks as formulated in Equation (22).

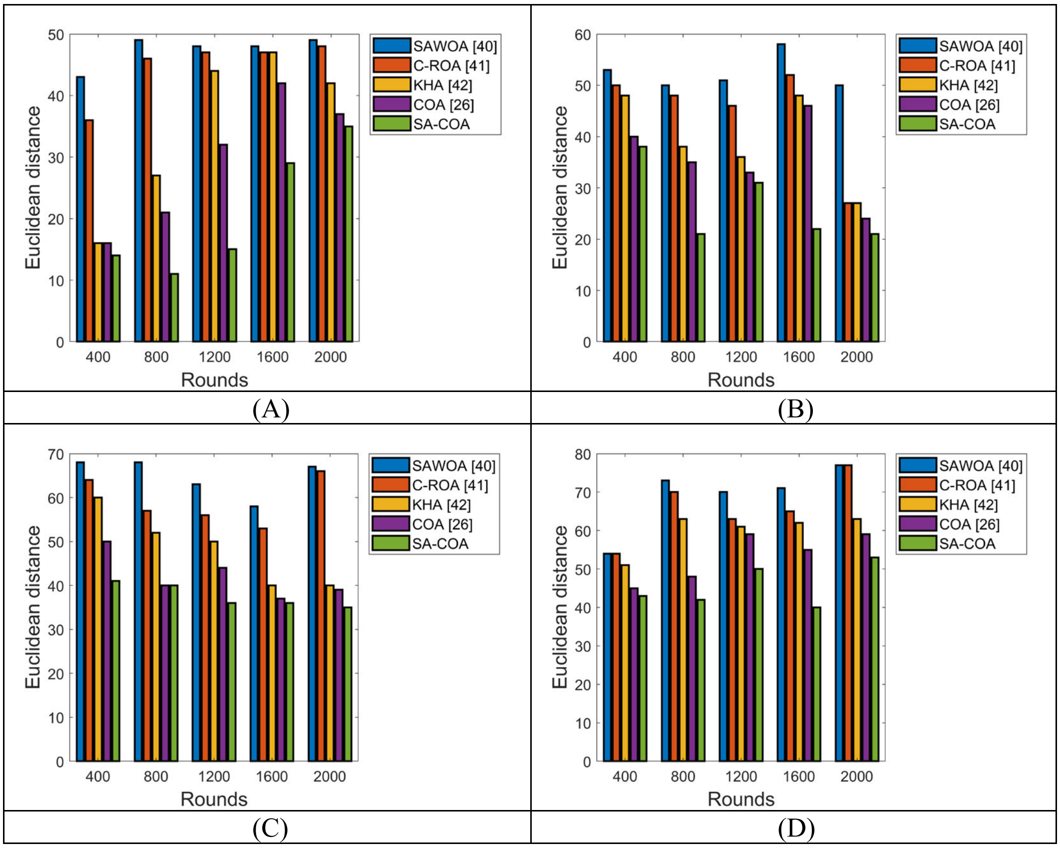

FIGURE 8 Analysis of Euclidean distance of the designed network energy optimization and intelligent routing in wireless sensor network (WSN) applicable for Internet of Things (IoT) over other optimization algorithms regarding varying the number of sensor nodes (A) 50, (B) 100, (C) 150, and (D) 200.

$$Th = \frac{\sum_{nd} a}{\sum_{nd} c} \tag{22}$$

Here, the number of demands is expressed as nd, a represents the "FTP download or upload in kilo-bit (kb) during one session," and c denotes "the time duration to upload or download a task output or task input." Further, residual energy is mentioned as En_{res} at any node No_n, which is derived in Equation (23). It is defined as "the average remaining energy of the active sensor nodes at the end of each simulation experiment."

$$En_{res(n)} = En_n - \left(en_n^{cs} + e_n^{sh}\right) \tag{23}$$

Here, the energy utilization by sending the number of data units is given as e_n^{sh}, the energy utilization by collecting the number of the data unit is given as en_n^{cs}, the residual energy of any node No_n is derived as En_n, and then, the lifetime of the network is noted as LN.

Network lifetime is "the total number of rounds of the mobile sink before the first node runs out of its energy." The network lifetime is formulated "from the link lifetime and should be maximal to attain effective routing."

6 | RESULTS

6.1 | Simulation evaluation

The performance of the designed method was developed in MATLAB 2020a, which will be compared with the baseline models regarding finding the number of alive nodes, distance, delay, residual energy, throughput, network lifetime,

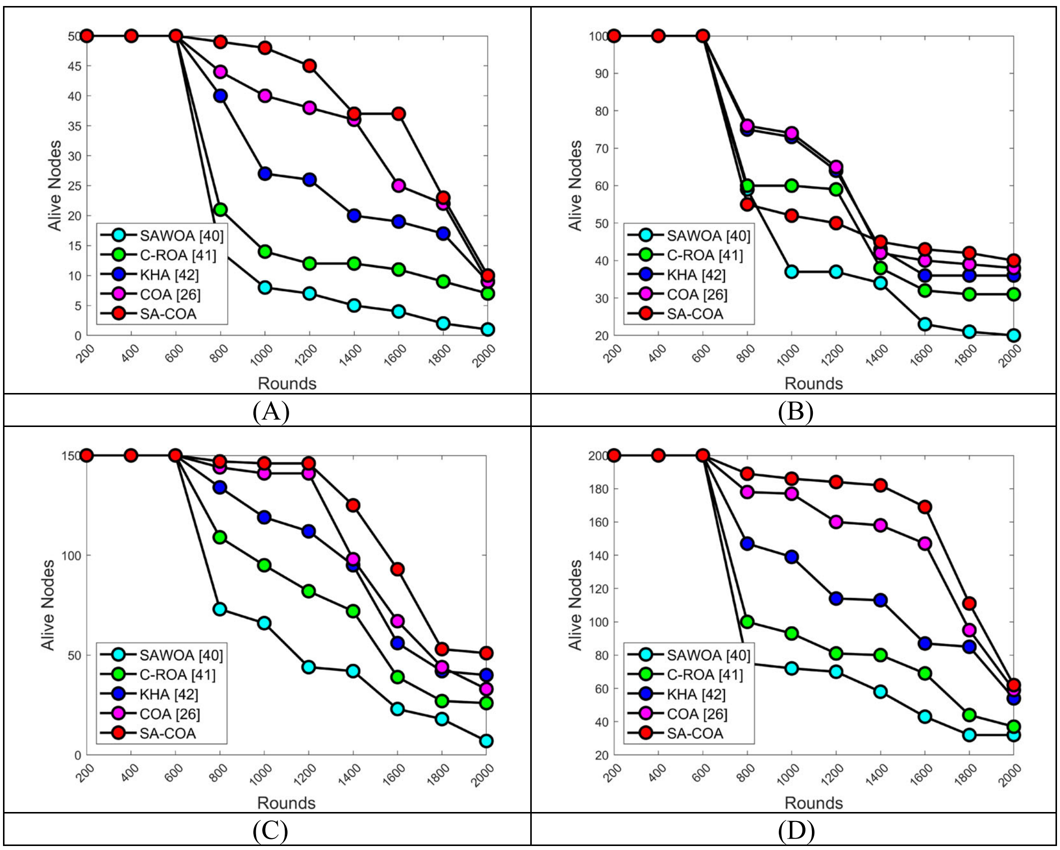

FIGURE 9 Estimation on alive nodes of the designed network energy optimization and intelligent routing in wireless sensor network (WSN) applicable for Internet of Things (IoT) over other heuristic algorithms regarding varying the number of sensor nodes (A) 50, (B) 100, (C) 150, and (D) 200.

and so on. The performance analysis was conducted over existing algorithms like self-adaptive whale optimization algorithm (SAWOA),[48] cyclic rider optimization algorithm (C-ROA),[49] krill herd algorithm (KHA),[50] and COA.[47] The constraints used for designing the proposed WSN model for IoT was given in Table 2.

6.2 | Convergence analysis

The efficiency of the offered WSN for the IoT method is validated in terms of cost function vs iterations as given in Figure 7. The minimum cost function is observed by SA-COA at initial iterations while comparing with other algorithms. Even if we enlarge the number of nodes from 50 to 200, the equivalent and superior performance are observed by the designed SA-COA-based network model. For example, while taking the count of nodes as 50 at the 10th iteration, the convergence analysis of SA-CSO is 70.2%, 61%, 53.3%, and 41.6% superior to SAWOA, C-ROA, KHA, and COA, respectively. Thus, the advanced convergence behavior is observed by the SA-COA-based network model.

6.3 | Estimation of distance

Evaluation of the designed network energy optimization and intelligent routing using SA-COA is depicted in Figure 8. The minimum distance attained by SA-COA shows a higher performance than other algorithms. While considering the number of nodes as 100 and the number of rounds as 2000, the Euclidean distance of SA-COA is 58%, 22.2%, 22.2%, and 16% advanced than SAWOA, C-ROA, KHA, and COA, respectively. Finally, superior performance is achieved by the SA-COA-based routing model when evaluated with other heuristic algorithms.

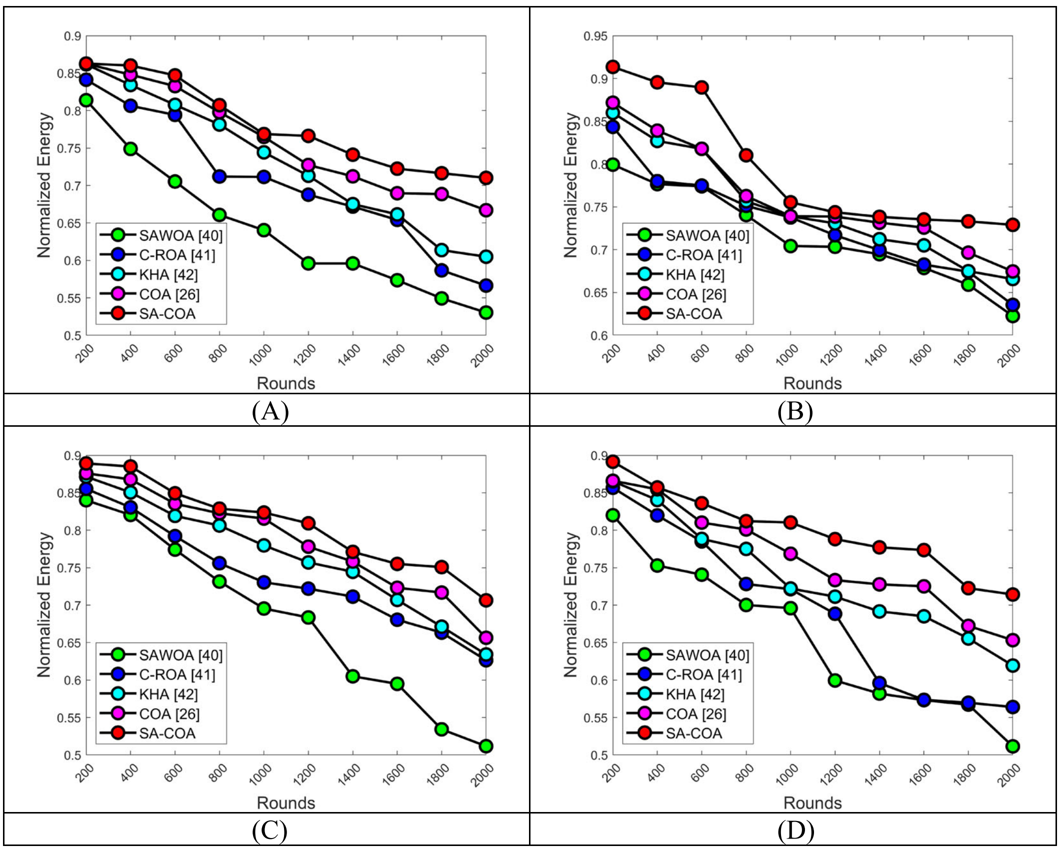

FIGURE 10 Estimation of normalized energy of the designed network energy optimization and intelligent routing in wireless sensor network (WSN) applicable for Internet of Things (IoT) over other heuristic algorithms regarding differing the number of sensor nodes (A) 50, (B) 100, (C) 150, and (D) 200.

6.4 | Analysis of alive nodes

Evaluation of the recommended network with SA-COA is analyzed over a count of alive nodes as given in Figure 9. The maximum number of alive nodes demonstrates the higher performance of the proposed SA-COA, and it specifies the higher convergence rate. While taking the number of nodes as 150 and the number of rounds as 1800, the performance of SA-COA gives 51.9%, 73.3%, 15.5%, and 13% progressed than SAWOA, C-ROA, KHA, and COA, respectively. Therefore, the maximum performance is attained by SA-COA-based intelligent routing when evaluating with other heuristic algorithms.

6.5 | Estimation of normalized energy

Estimation of normalized energy of the developed intelligent routing in WSN applicable for IoT by differing the count of rounds is depicted in Figure 10. The SA-COA-based network model shows the higher normalized energy when varying the number of nodes. While taking the number of nodes as 200 and the number of rounds as 2000, the normalized energy of the designed SA-COA gets 42%, 28.8%, 14.5%, and 9.2% better than SAWOA, C-ROA, KHA, and COA, respectively. Similarly, the higher efficiency is examined by SAWOA when compared with existing optimization algorithms.

6.6 | Analysis of residual energy

Evaluation of the offered network energy optimization and SA-COA-based routing is estimated regarding residual energy as given in Figure 11. The higher efficiency regarding residual energy by SA-COA specifies the higher network

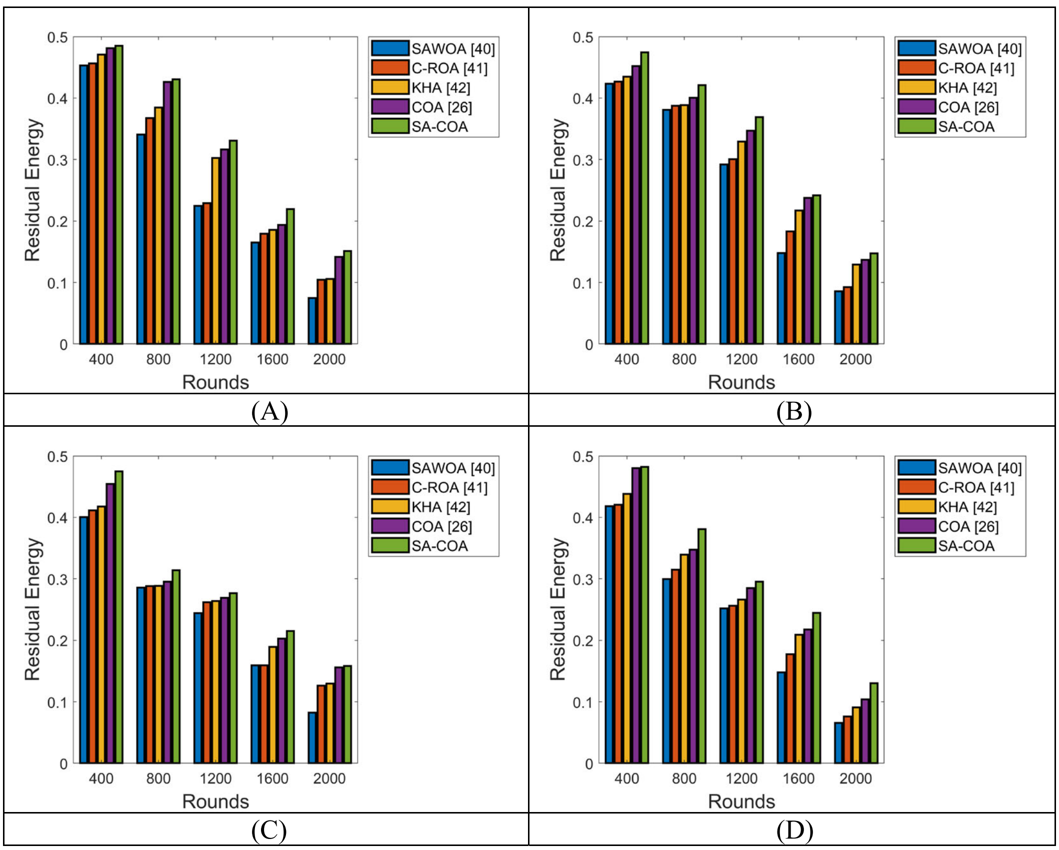

FIGURE 11 Estimation of residual energy of the designed network energy optimization and intelligent routing in wireless sensor network (WSN) applicable for Internet of Things (IoT) over other heuristic algorithms regarding varying the number of sensor nodes (A) 50, (B) 100, (C) 150, and (D) 200.

efficiency while comparing with existing algorithms. When taking the number of nodes as 50 and the number of rounds as 1200, the residual energy of the SA-COA achieves 47.8%, 44.6%, 13.3%, and 6.25% maximized than SAWOA, C-ROA, KHA, and COA, respectively. Hence, the optimal performance regarding residual energy is attained by SA-COA.

6.7 | Estimation of throughput

Evaluation of the suggested network energy optimization method is validated regarding throughput as given in Figure 12. The high performance is achieved by getting a higher throughput using SA-COA, and thus, superior efficiency is ensured. While taking the number of rounds as 1200 and considering the number of nodes as 100, the throughput of SA-COA is 71.4%, 42.8%, 36.3%, and 9% higher than SAWOA, C-ROA, KHA, and COA, respectively. Thus, the optimal performance is attained by SA-COA by estimating with existing algorithms.

6.8 | Analysis of time complexity

The evaluation of the designed network energy optimization model regarding time complexity is given in Figure 13. The minimum time complexity is attained by SA-COA while analyzing with other heuristic algorithms. While taking the count of nodes as 150 and the number of rounds as 400, the time complexity of SA-COA is 26%, 18%, 8.8%, and 6.8% more advanced than SAWOA, C-ROA, KHA, and COA, respectively. So, the offered method outperforms the existing models in terms of minimum time complexity, and hence, it gets superior performance.

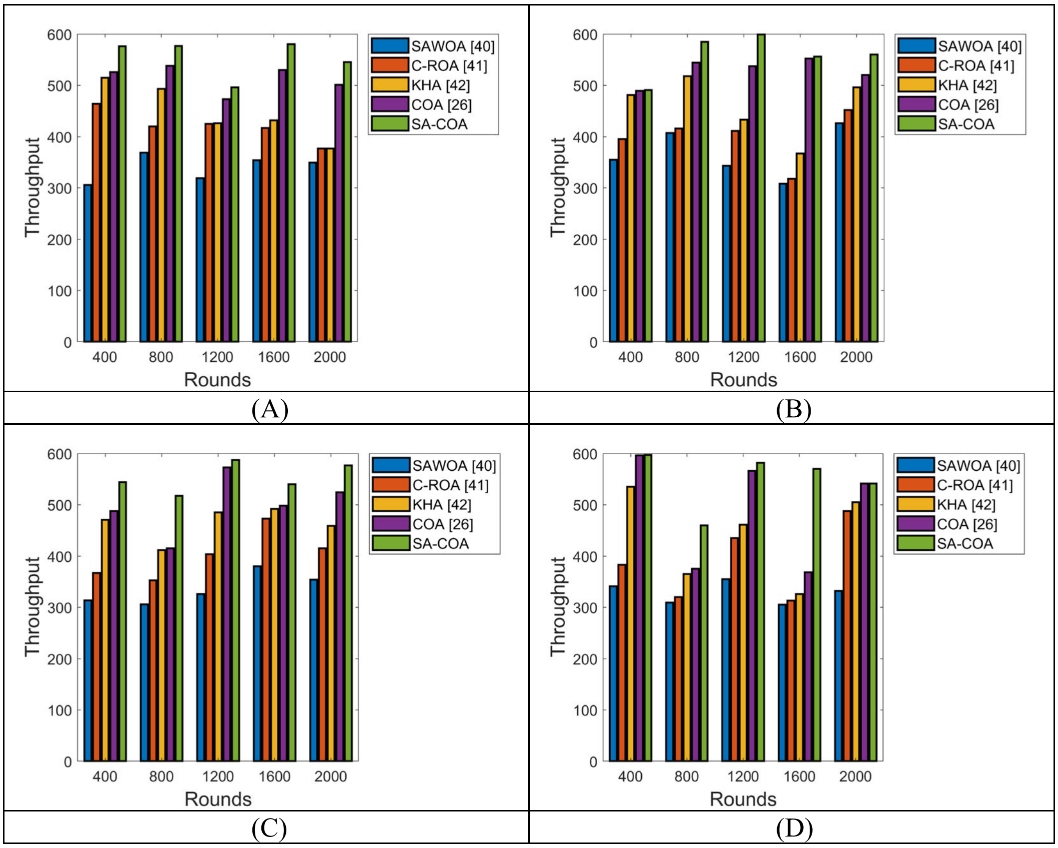

FIGURE 12 Evaluation of throughput of the designed network energy optimization and intelligent routing in wireless sensor network (WSN) applicable for Internet of Things (IoT) over other heuristic algorithms regarding differing the number of sensor nodes (A) 50, (B) 100, (C) 150, and (D) 200.

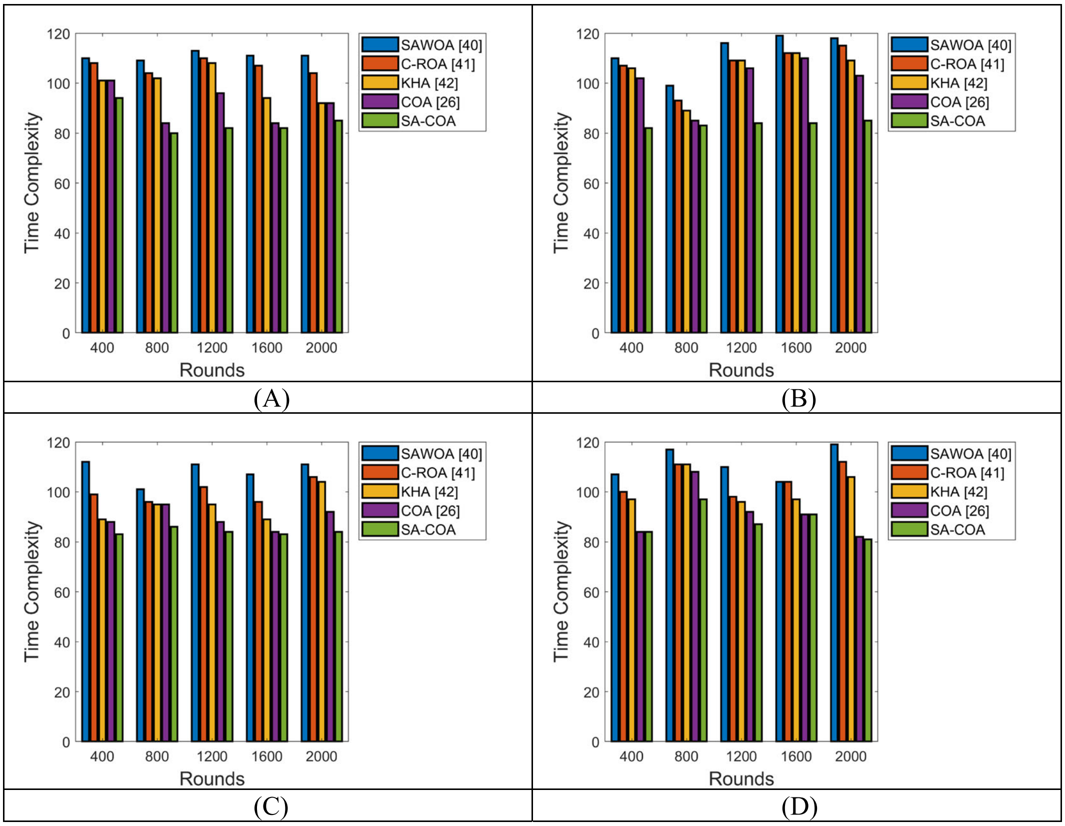

FIGURE 13 Analysis of time complexity of the designed network energy optimization and intelligent routing in wireless sensor network (WSN) applicable for Internet of Things (IoT) over other heuristic algorithms in terms of varying the number of sensor nodes (A) 50, (B) 100, (C) 150, and (D) 200.

6.9 | Overall performance analysis

Evaluation of the suggested network model is depicted in Table 3 by varying the number of rounds. The designed SA-COA-based LEACH routing outperforms the standard LEACH protocol, which shows competitive performance.

TABLE I.

6.10 | Time complexity of the proposed algorithm

The time complexity of the proposed SA-COA model is shown in Table 4. Here, the term *iter* is defined as the number of iterations, and also, the term N_{pop} is the number of populations. The term *chlen* is defined as the chromosome length.

6.11 | Findings of the confidence interval of the proposed approach

The findings of the confidence interval of the designed network energy optimization and intelligent routing in WSN applicable for the IoT model are shown in Table 5.

TABLE 3 Performance analysis on proposed network energy optimization and intelligent routing in wireless sensor network (WSN) applicable for Internet of Things (IoT) model by varying the rounds.

Number of rounds	LEACH	SA-COA-LEACH
Number of nodes 50		
200	62.88	58.009
400	65.783	61.397
600	68.494	64.283
800	71.448	67.668
1000	74.78	70.609
1200	78.012	73.471
1400	80.77	76.554
1600	84.033	79.248
1800	87.02	82
2000	89.997	84.977
Number of nodes 100		
200	72.837	68.104
400	75.839	71.092
600	79.257	74.299
800	82.37	77.203
1000	85.524	80.138
1200	88.44	83.062
1400	91.264	85.969
1600	94.158	88.806
1800	97.052	91.988
2000	99.996	94.992
Number of nodes 150		
200	83.14	77.785
400	85.957	80.388
600	88.806	83.293
800	91.847	87.138
1000	94.85	90.077
1200	97.552	93.282
1400	100.66	96.479
1600	103.82	99.374
1800	107.26	102.41
2000	109.98	104.99
Number of nodes 200		
200	93.455	87.889
400	96.783	90.816
600	99.452	93.615
800	102.5	96.494
1000	105.09	99.421
1200	108	102.55
1400	111.25	105.63
1600	114.28	108.85

(Continues)

TABLE 3 (Continued)

Number of rounds	LEACH	SA-COA-LEACH
1800	117.02	111.94
2000	120	114.99

TABLE 4 The time complexity of the proposed self-adaptive coyote optimization algorithm (SA-COA) model.

The time complexity of SA-COA	$O\left[iter^{*} N_{pop}{}^{*}(chlen)\right]$

TABLE 5 Findings of the confidence interval of the designed network energy optimization and intelligent routing in wireless sensor network (WSN) applicable for the Internet of Things (IoT) model.

Node 50	45.9906, 66.9276
Node 100	52.0109, 72.2809
Node 150	43.554, 65.7046
Node 200	40.8854, 68.5422

TABLE 6 Statistical analysis of the designed network energy optimization and intelligent routing in wireless sensor network (WSN) applicable to the Internet of Things (IoT) model.

Algorithms	SAWOA[41]	C-ROA[42]	KHA[43]	COA[29]	SA-COA
Number of nodes 50					
Best	33.117	33.812	33.133	35.331	32.739
Worst	80.541	89.392	84.105	78.866	83.102
Mean	56.459	63.909	60.594	55.582	51.221
Median	58.903	65.844	59.861	55.639	41.329
Standard Deviation	14.634	20.284	18.463	13.525	19.857
Number of nodes 100					
Best	31.697	33.622	38.016	31.193	30.61
Worst	87.608	86.587	85.136	86.717	83.268
Mean	63.966	58.443	61.004	59.221	62.146
Median	72.657	59.341	60.705	56.9	66.019
Standard Deviation	20.027	20.312	14.639	17.664	14.168
Number of nodes 150					
Best	33.303	37.875	47.058	31.358	30.014
Worst	89.278	83.183	85.506	85.437	82.111
Mean	59.763	54.629	67.173	50.689	52.58
Median	60.766	51.442	66.865	53.68	46.974
Standard Deviation	20.266	15.482	14.097	18.109	17.574
Number of nodes 200					
Best	45.009	34.049	34.713	44.256	30.167
Worst	89.035	86.846	88.242	87.9	78.915
Mean	72.485	54.714	67.009	69.57	48.181
Median	72.084	48.673	73.254	70.195	45.045
Standard Deviation	13.432	19.331	17.761	15.419	15.654

Abbreviations: COA, coyote optimization algorithm; C-ROA, cyclic rider optimization algorithm; KHA, krill herd algorithm; SA-COA, self-adaptive coyote optimization algorithm; SAWOA, self-adaptive whale optimization algorithm.

6.12 | Evaluation of statistical analysis of the designed method

Evaluation of the statistical analysis for the designed network energy optimization and intelligent routing in WSN applicable to the IoT model is shown in Table 6. The best value of the designed SA-COA-LEACH model is secured at 1.14%, 3.17%, 1.18%, and 7.33% progressed than SAWOA, C-ROA, KHA, and COA while taking several nodes 50. Accordingly, the median values of the designed SA-COA-LEACH are secured at 37.51%, 7.45%, 38.50%, and 35.82% progressed than SAWOA, C-ROA, KHA, and COA while taking several nodes 200. Thus, the simulation findings of the designed SA-COA-LEACH model achieve better results than the other baseline approaches.

7 | CONCLUSION

This model has focused on implementing a new CH selection model in WSN applicable for IoT using the self-adaptive meta-heuristic algorithm, which has also introduced the concept of selecting the direct nodes, CH, and CCH in the sensor network through SA-COA. The direct node selection was done by minimizing the mean energy and Euclidean distance among nodes. Further, the CH selection was carried out by correlating the threshold value with residual energy. Further, the CCH selection by SA-COA has been suggested by resolving the fitness function with constraints like Euclidean Distance, throughput, network lifetime, delay, and remaining energy of the node. Thus, finally, the modified LEACH protocol with SA-COA has ensured the optimal efficiency regarding simulation results. The convergence analysis of the offered method using SA-COA was 66.6%, 60%, 53.3%, and 44% maximized than SAWOA, C-ROA, KHA, and COA, respectively while considering the number of nodes as 50 at the 10th iteration. Finally, the superior effectiveness and reliability of the proposed routing algorithm were ensured in sensor networks than the existing methods. It is utilized to improve energy efficiency. The applications of this designed method are environmental monitoring advanced healthcare delivery, industrial process control, and multimedia surveillance. The sensor nodes are presented in a non-rechargeable battery with limited energy storage capabilities. Moreover, a few limitations are discussed as follows. A lot of applications are there for a virtually infinite lifetime. However, energy scarcity is the major issue for this designed method. A variety of energy-aware network protocols will be developed to manage the limited energy resources, which helps to extend the lifetime of an offered method. Additionally, two aspects of delay reduction will be adopted with the shortest path concept, which allows for avoiding node delay. The synchronous and asynchronous mechanisms will be implemented in the future.

DATA AVAILABILITY STATEMENT

Data sharing not applicable to this article as no datasets were generated or analysed during the current study.

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