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Chronological wild geese optimization algorithm for cluster head selection and routing in wireless sensor network

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Summary

Wireless sensor networks (WSNs) consist of numerous sensor nodes with limited battery life, computational power, and network capabilities. These sensors are deployed in specific areas to monitor environmental physical parameters. Once the data are collected, it is processed and transmitted to a base station (BS) via designated routes. The processes of sensing and transmitting consume significant energy, leading to rapid depletion of node batteries and the occurrence of hot spot problems. Consequently, relying on a single route for data transmission can result in network overhead issues. Enhancing the energy efficiency of WSNs is a persistent challenge. To address this, improvements in processes, such as routing and clustering are necessary. Implementing dynamic cluster head (CH) selection is a key approach for optimal path selection and energy conservation. Accordingly, in this work, a novel multiobjective CH selection and routing method for providing energy-aware data transmission in WSN is presented. Here, CH selection is carried out using the proposed chronological wild geese optimization (CWGO) technique based on multiple constraints, such as delay, intercluster distance, intracluster distance, Link Life Time (LLT), and predicted energy. Further, the nodes' energy is determined by the deep recurrent neural network (DRNN). Then, the ideal path from the node to the BS is identified by the CWGO considering constraints, like predicted energy, delay, distance, and trust. Moreover, the proposed CWGO is examined considering metrics, like energy, trust, distance, and delay and is found to have attained superior values of 0.963 J, 0.700, 19.468 m, and 0.252 s, respectively.

KEYWORDS

chronological concept, chronological wild geese optimization, deep recurrent neural network, multiobjective routing, wild geese algorithm

1 | INTRODUCTION

The swift advancement in wireless communication technologies has resulted in wireless sensor network (WSN) being utilized in various domains, like military fields, different commercial applications, intelligent agriculture, medical care, emergency rescue, and environmental monitoring.[1] WSNs are suitable to be applied in hard surroundings where installation of wired networks is impossible. They can also be used in areas where collecting data manually is infeasible or dangerous and artificial intelligence (AI)-based node location can be computed.[2] WSN is a network that is self-organizing and comprises numerous homogeneous sensor nodes with restricted energy installed in comparatively harsh environments, terminal systems, and base station (BS) or sinks.[1,3] Sensor nodes are employed for sensing information from their detection area and transmit the information to the BS. The information is accessed over the internet from the sink by end users. The sensor nodes or sink can be dynamic or static based on the applications for which the network is created. Generally, the sensor nodes have restricted resources, such as batteries, transceivers, sensing units, and small processors. Among the various resources, the battery is deemed to be a critical component as no recharging and replacement at distinct intervals is possible especially if the sensors are deployed in inaccessible places.[4] The sensors have a tiny battery using which multiple functions, like information processing and communication, are performed. This will lead to failures in the network or a reduction in the life expectancy of the network.[5,6] Hence, maintaining energy efficiency is significant while transmitting data to extend the lifetime of WSN.[7]

Energy preservation is the key substantial aspect for sensor nodes in WSN to extend their lifetime. A major portion of the energy is utilized while transmitting and receiving packets. As a number of devices are connected together and it is challenging to charge batteries, the capacity of the battery is considered a highly significant resource in WSN,[8] thereby making the minimization of energy a crucial problem.[9] As the node gets depleted of its energy, it ceases data transmission, and this process is termed the “death” of the node. While multiple “dead” nodes exist in the network, the WSN is no longer connected leading to the eventual “paralysis” of the network.[10,11] Thus, it is critical to minimize energy utilization for prolonging the life expectancy of WSNs.[12] In order to attain this objective, effective routing protocols can be used, which can contribute a significant part and in the last few years, numerous energy-efficient routing techniques have been developed. A most commonly used technique is grouping the sensor nodes in a cluster to achieve an energy-efficient balanced routing.[13,14] The clustering techniques function in iterations, every iteration containing two stages: formation and stabilization. At first, the nodes are arranged into diverse clusters or groups.[9] All clusters have a cluster head (CH) and numerous ordinary nodes known as cluster members (CMs). At CH in a cluster, data aggregation is accomplished and the aggregated data are forwarded to the BS. Clustering is beneficial in minimizing the communication overhead, which reduces the overall energy utilization of the network.[4]

In WSN, clustering-based techniques minimize the overall number of data transmissions using intercluster and intracluster communications.[15] But the effectiveness of the clustering techniques relies on the manner in which CH is selected, together with the way in which the optimal cluster count is formed. Energy consumption can be mitigated by performing clustering optimally as it can replace one-hop communication between CH to BS with an ideal multihop distance.[16] With the intention of balancing the energy-efficiency ratio of WSNs,[17,18] it is essential to choose the ideal CH with the best capabilities. Thus, few of the computational intelligence (CI) and metaheuristic algorithms, such as evolutionary algorithms, reinforcement learning (RL), artificial immune systems (AIS), and artificial bee colony (ABC), are employed to carry out clustering considering it an NP-hard optimization problem.[19] Recently, several studies[20,21] have been performed based on optimizing energy consumption while selecting the route in WSN, with a major focus on CH multihop hybrid routing considering cluster structure.[22] The nodes are initially clustered in the neighborhood, and the information accumulated is assimilated at the CH, which transmits the information to the BS using multiple hops among CH in hybrid routing.[23] This type of routing protocol can effectively simplify the structure of the network and evade energy consumption funnels and hotspots. In hybrid routing protocols, CH is regarded as the key node.[24] The total energy utilization of the network can be effectively determined on the basis of CH selection and the identification of multihop routes among the CH.[25,26]

1.1 | Problem statement and motivation

In WSN, the sensor nodes have restricted resources, and it is infeasible to recharge or replace the batteries. In such scenarios, it is essential to develop techniques for achieving energy efficiency. Although clustering and routing are deemed the most effective approach for lengthening the life expectancy of WSN, choosing the ideal CH and route are still challenging tasks. The issues confronted by the various prevailing methods for CH selection and routing in WSN are enumerated as follows:

- The main issue confronted by the EECHIGWO technique proposed in Rami Reddy et al.[16] is that though the technique was efficient in reducing the premature death rate of sensor nodes, it failed to consider a WSN with high node density and a large count of sensor nodes, thus limiting its application in large-scale networks. The developed

method is applicable to large-scale networks since it takes into account a WSN with a high node density and a high number of sensor nodes.
- The DUCISCA developed in Zhu and Wang[1] was effective in extending the lifespan and multiple CHs were able to transmit information to the BS indirectly using the enhanced multihop routing. However, no optimization technique was considered to enhance the energy-saving effect of the method. In the devised method, a hybrid optimization approach called CWGO is developed, which enhance the energy-saving effect of the method.
- A hybrid routing algorithm based on Naïve Bayes and improved particle swarm optimization (HRA-NP) in WSN is developed in Wang et al.[26] This scheme was effective in minimizing the energy consumption and quantity of data transmitted. However, the HRA-NP did not consider delay and other features for augmenting the network efficiency. In the proposed method, delay and other features are considered for augmenting the network efficiency.

The energy efficiency of the WSN can be augmented by using efficient CH selection and routing schemes, and in this work, an energy-aware routing technique is presented. Here, simulation of the WSN is carried out first and the network is modeled based on three models, such as energy, LLT, and trust. Further, the finest node is selected as a CH using the proposed CGWO based on a multiobjective function formulated taking into account parameters, like LLT, delay, predicted energy, and intracluster and intercluster distance. Here, the energy available at the nodes is estimated using the DRNN. Thereafter, the ideal route from the node to the BS is found by applying the CGWO considering parameters, such as distance, delay, trust, and predicted energy.

The chief contribution of this research is explicated below:

- **Proposed CWGO for CH selection and routing**: A hybrid optimization approach called CWGO is developed by integrating the chronological concept in the wild geese algorithm (WGA). Here, CH selection is accomplished by the CWGO on the basis of LLT, delay, predicted energy, and intracluster and intercluster distance, and routing is performed based on attributes, such as distance, trust, delay, and predicted energy.

The structural arrangement of the remaining part of the study is as ensuing: Section 2 deliberates the related works, the system model of the WSN is detailed in Section 3, Section 4 expounds on the proposed CWGO, Section 5 presents a detailed assessment of the experimental results, and Section 6 concludes the research.

2 | RELATED WORKS

In this section, some of the related works are expounded, which stimulated the inception of the CWGO. Rami Reddy et al.[16] developed an Energy-Efficient CH selection approach with an Improved Gray Wolf Optimization (EECHIGWO). This technique was mainly used to enhance the network lifespan, stability, average throughput, and energy efficiency. Further, the EECHIGWO selected the CH by considering various parameters, like residual energy, intracluster distance, CH balancing factor, and sink distance. The EECHIGWO was successful in improving the stability and throughput of the WSN, but the approach was futile in considering heterogeneous nodes. Zhu and Wang[1] developed a distributed energy-balanced unequal clustering routing protocol with an improved sine cosine algorithm (DUCISCA) for multihop routing. This method was a distributed competition technique, which utilized competition among the nodes to select the CH. Here, the nodes competed unequally depending on the distance and available energy from the BS, thereby balancing the energy utilization of the nodes at varied positions. The multihop path was determined by using the improved sine-cosine algorithm (ISCA) with adaptive mutation and Latin hypercube sampling. This scheme reduced the overhead of nodes and minimized energy consumption effectively but the method had a slightly higher death speed. Hossan and Choudhury[4] proposed a distance and energy aware stable election routing protocol (DE-SEP) for conserving energy in WSN. Here, CH selection was made considering the distance and energy so that the nodes closer to the BS and with high energy are chosen as CH. Further, it avoided redundant cluster formation by limiting the CH count, thus minimizing energy utilization. The DE-SEP protocol was successful in minimizing the death rate of the nodes and was effectual in improving energy efficiency even as the network size increased. This method suffered from degraded stability as the separation between the CH to other member nodes and BS increased. Xue et al.[2] developed a cross-layer-based Harris-hawks-optimization (CL-HHO) routing approach for minimalizing power consumption and transmission delay in WSN. Here, clustering was accomplished in an energy-efficient manner using the K-medoids with improved artificial-bee-colony (K-IABC), and routing was carried out using the CL-HHO method. This model was successful in enhancing the network restructuring while the energy-hole scenario was encountered. However, the method required a large number of iterations to determine the optimal transmission path.

Cherappa et al.[9] created an energy-efficient cross-layer-based expedient routing protocol (E-CERP) for decreasing latency, and distance, and achieving energy stabilization. Here, K-medoids with adaptive sailfish optimization (K-ASFO) was employed for clustering the sensor nodes, and the optimal route was identified using the E-CERP approach. The method determined the shortest path and provided reliable communication, although only static nodes were considered. Vellaichamy et al.[7] developed a Combined Bio-Inspired Algorithm for determining the routing path in WSN in an energy-efficient way. Further, a multiconstraint clustering technique was developed for identifying the ideal CH. Here, a combined bio-inspired algorithm was created by utilizing the salp swarm and moth flame optimizations. This scheme was successful in attaining a good packet delivery rate and minimum energy utilization; however, it was futile in attaining a substantial reduction in the end-to-end delay as the node size increased. Wu et al.[27] developed a dual CH energy-efficient algorithm named Dual CH, canopy optimization, and *K*-means algorithm—low-energy adaptive clustering hierarchy (DCK-LEACH) for WSN. Here, clustering was accomplished using the *K*-means and canopy optimization for selecting the CHs in a hierarchical manner. Here, two CHs, such as the primary and secondary, were considered for balancing the load. The DCK-LEACH technique had good scalability and was effective in adapting to variations in the node density of WSN. However, the technique failed to boost the network's throughput. Wang et al.[26] created a hybrid routing algorithm based on Naïve Bayes and improved particle swarm optimization (HRA-NP) in WSN. Here, the Naïve Bayes classifier was employed to estimate the CH conditional probability depending on which CH was selected. Further, an improved particle swarm optimization (PSO) technique was utilized to find the ideal routing path. This scheme was effective in minimizing the energy consumption and quantity of data transmitted. But the HRA-NP did not consider delay and other features for augmenting the network efficiency. Jagan and Jesu Jayarin[28] suggested a fully connected energy efficient clustering (FCEEC) mechanism that creates a fully connected network with shortest path routing from sensor nodes (SNs) to cluster head (CH) in a multihop environment by utilizing the electrostatic discharge algorithm. The suggested electrostatic discharge algorithm (ESDA) achieves energy-efficient complete connection between sensor nodes while prolonging the life of the network. Dass et al.[29] suggested the secure optimal path-routing (SOPR) protocol, a brand-new cluster-based secure routing technology. To improve communication security in WBANs, this suggested technique strengthens security by, on the one hand, recognizing and avoiding black-hole attacks and, on the other, transmitting data packets in encrypted form. Improving overall network performance by raising the packet-delivery ratio and decreasing attack-detection overheads, detection time, energy consumption, and latency are the primary benefits of putting the suggested protocol into practice. Table 1 shows the review of existing methods.

3 | WSN MODEL

The WSN[30] encompasses multiple nodes that are arbitrarily dispersed, and these nodes sense, process, and transmit the data to the BS via a CH. Consider there are a total of a nodes in the WSN, and the nodes are grouped under a cluster referred as Z_i. These nodes transmit data to the sink node BS, and the information is transmitted based on the uniform distribution with maximal radio level in the dimension $S_i \times S_j$. Every cluster is associated with a CH indicated as M_z^i, and the data are routed to the BS from all nodes using a CH-based routing technique. Here, the r^{th} CH is considered to be at a distance l_{MB} from the BS and the distance to the s^{th} normal node is termed as l_{rs}. This scheme provides the benefit of improving the lifespan and a structured data flow. In addition to this, the performance of the WSN is improved by considering constraints, like predicted energy, delay, intracluster and intercluster distances. Figure 1 exhibits the system model of the WSN. Table 2 shows the notation of the WSN model.

3.1 | Energy model

Energy[31] is a significant parameter in WSN, as the lifetime of the network depends on the energy availability of the nodes. The nodes dissipate energy while it transmits and receives data and the energy expended during these processes can be modeled as

TABLE 1 Review of existing methods.

Authors	Methods	Advantages	Disadvantages
Rami Reddy et al.[16]	EECHIGWO	The EECHIGWO was successful in improving the stability and throughput of the WSN	The approach was futile in considering heterogeneous nodes.
Zhu and Wang[1]	DUCISCA	This scheme reduced the overhead of nodes and minimized energy consumption effectively.	The method had a slightly higher death speed.
Hossan and Choudhury[4]	DE-SEP	The DE-SEP protocol was successful in minimizing the death rate of the nodes and was effectual in improving energy efficiency even as the network size increased.	This method suffered from degraded stability as the separation between the CH to other member nodes and BS increased.
Xue et al.[2]	CL-HHO	This model was successful in enhancing the network restructuring while the energy-hole scenario was encountered.	The method required a large number of iterations to determine the optimal transmission path.
Cherappa et al.[9]	E-CERP	The method determined the shortest path and provided reliable communication.	Here only static nodes were considered.
Vellaichamy et al.[7]	Combined Bio-Inspired Algorithm	This scheme was successful in attaining a good packet delivery rate and minimum energy utilization.	It was futile in attaining a substantial reduction in the end-to-end delay as the node size increased.
Wu et al.[27]	Dual CH energy-efficient algorithm	The DCK-LEACH technique had good scalability and was effective in adapting to variations in the node density of WSN.	The technique failed to boost the network's throughput.
Wang et al.[26]	HRA-NP	This scheme was effective in minimizing the energy consumption and quantity of data transmitted.	The HRA-NP did not consider delay and other features for augmenting the network efficiency.
Jagan and Jesu Jayarin[28]	FCEEC	The suggested electrostatic discharge algorithm (ESDA) achieves energy-efficient complete connection between sensor nodes while prolonging the life of the network.	-
Dass et al.[29]	SOPR	Improving overall network performance by raising the packet-delivery ratio and decreasing attack-detection overheads, detection time, energy consumption, and latency are the primary benefits of putting the suggested protocol into practice.	-

$$\xi_{tr}(p,l) = \xi_{ele} * p + \xi_{amp} * p * l^2 \tag{1}$$

$$\xi_{rx}(p) = \xi_{ele} * p \tag{2}$$

where ξ_{tr} represents the energy dissipated by the transmitter, ξ_{ele} indicates the electronic energy, p specifies the number of bits in the message, ξ_{amp} symbolizes the propagation constant, l refers to the distance between the receiver and the transmitter, and ξ_{rx} is the energy dissipated by the receiver.

3.2 | LLT model

Apart from energy, the lifetime of the WSN is influenced by LLT[32] as it determines the reliability of the network. The dynamic nature of the WSN necessitates the determination of the reliability of the route in a dynamic manner. The LLT is calculated at every hop in the route through which the route request packet (RRP) traverses. Consider two nodes r and s whose coordinates are (x_r, y_r) and (x_s, y_s) lying in the communication region. The LLT is measured by a specific node based on the life expectancy of the link connecting the node with its earlier hop and is formulated as

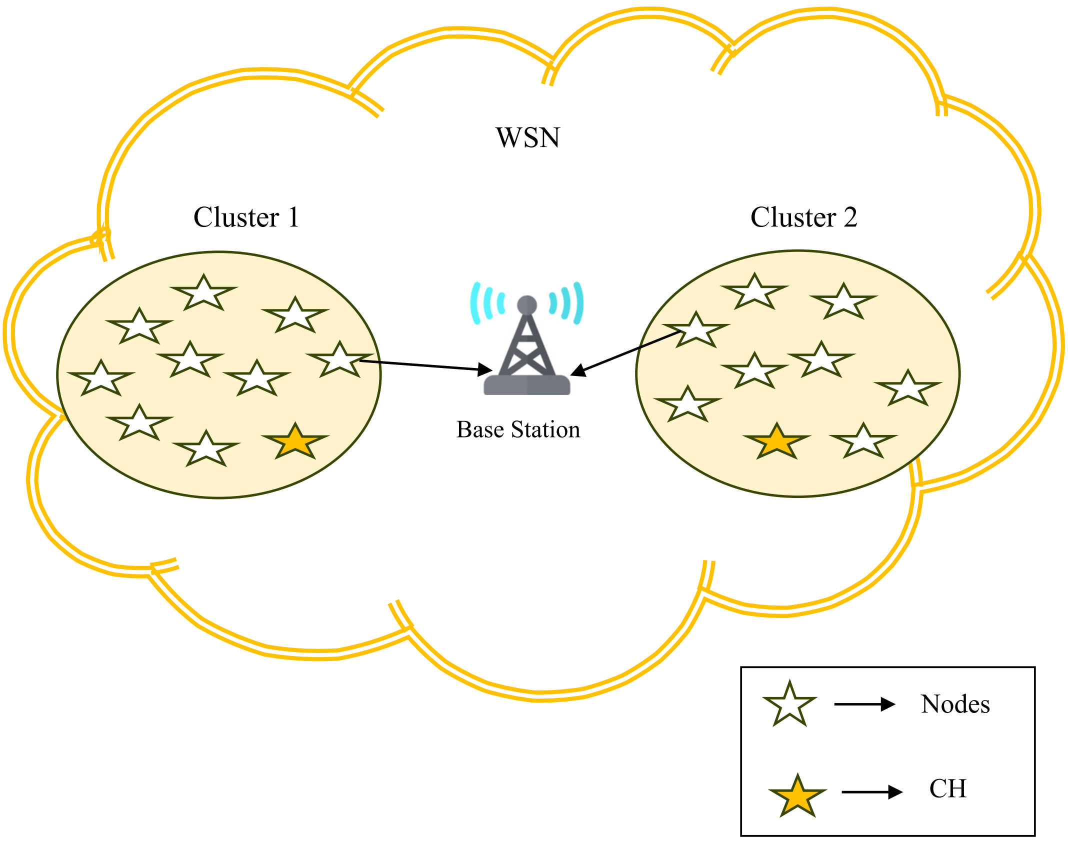

FIGURE 1 System model of WSN.

TABLE 2 Notation of the WSN model.

Notation	Definition
ξ_{tr}	Energy dissipated by the transmitter
ξ_{ele}	Electronic energy
p	Number of bits in the message,
ξ_{amp}	Propagation constant,
l	The distance between the receiver and the transmitter
ξ_{rx}	Energy dissipated by the receiver.
λ_r and λ_s	The mobility rate of nodes r and s.
ψ_r and ψ_s	The distance moved by the nodes r and s.
t	Time
t_{ant} and t_{approx}	The anticipated and approximate time required for authentication,
d	The number of neighboring nodes between the nodes r and s,
$IT_r^s(t)$	The IT that the node r has on the node s at the t^{th} instant.
ρ	The nodes' witness factor
$DT_r^s(t)$	The DT which the node r has on the node s at instance t.
ET_j	To the error in the j^{th} transaction, which can have a value of 1 or 0 depending on the error value,
κ	The number of transactions.

$$LLT = \frac{-(bc+gh)+\sqrt{\left(b^2+c^2\right)\gamma^2-(bh-cg)^2}}{\left(b^2+c^2\right)} \tag{3}$$

where $b=\lambda_r\cos\psi_r-\lambda_s\cos\psi_s$, $c=x_r-x_s$, $g=\lambda_r\sin\psi_r-\lambda_s\sin\psi_s$, and $h=y_r-y_s$, λ_r and λ_s refer to the mobility rate of nodes r and s, ψ_r and ψ_s represents the distance moved by the nodes r and s.

3.3 | Trust model

Another important aspect that has to be taken into account is to measure the trust[33] of the nodes. It is essential to determine the trustworthy nodes in the network so as to ensure that malicious nodes do not take part in routing. After the trust value is measured, these values are updated in the trust table, and communication is carried out based on the trustworthiness of the node. Three kinds of trust, namely, direct trust (DT), indirect trust (IT), and error-based trust (ET) are considered in this work.

a. DT

DT is based on the trust that a node r has on a node s, and this is determined by computing the time taken for communication among the nodes r and s. The DT is calculated in scenarios when the nodes often communicate with one another and is formulated as

$$DT_r^s(t)=\frac{1}{3}\left[DT_r^s(t-1)-\left(\frac{t_{approx}-t_{ant}}{t_{approx}}\right)+\rho\right] \tag{4}$$

2Here, t refers to the time, t_{ant} and t_{approx} stipulates the anticipated and approximate time required for authentication, ρ specifies the nodes' witness factor, and $DT_r^s(t)$ terms the DT which the node r has on the node s at instance t.

b. IT

In case the nodes do not communicate directly, then a witness factor between the nodes does not exist and in such scenarios, the trust between the nodes is computed by utilizing the DT of the neighboring nodes and it is known as IT. IT is computed by

$$IT_r^s(t)=\frac{1}{d}\sum_{j=1}^{d}DT_j^s(t) \tag{5}$$

where d indicates the number of neighboring nodes between the nodes r and s, and $IT_r^s(t)$ terms the IT that the node r has on the node s at the t^{th} instant.

c. ET

ET is determined by considering the error in communication, and it is formulated as depicted below.

$$ET_r^s(t)=\frac{1}{\kappa}*\sum_{j=1}^{\kappa}ET_j \tag{6}$$

where ET_j refers to the error in the j^{th} transaction, which can have a value of 1 or 0 depending on the error value, and κ represents the number of transactions.

4 | PROPOSED CWGO-ROUTING FOR CH SELECTION AND ROUTING

Energy consumption is a crucial aspect, which has to be carefully addressed for boosting the life expectancy of the WSN. This research proposes a multiobjective CH selection and routing method for providing energy-aware data transmission in WSN. The proposed technique is realized in the following manner. At first, the simulation of the WSN is accomplished, wherein the nodes and CH will be considered as moving nodes. Here, the WSN is simulated considering the link life time (LLT) model, mobility model, energy model, and trust model. Further, the energy at the nodes is predicted ahead of CH selection using a DRNN.[34] Thereafter, the ideal node is chosen as the CH using a multiobjective based optimization technique, wherein multiobjectives, like delay, intercluster distance, LLT, intracluster distance, and predicted energy are considered. The CH selection is performed with the help of the proposed CWGO algorithm, which is devised by combining the WGA[35] and chronological concept. Afterward, the ideal transmission path is determined by carrying out routing with the proposed CWGO algorithm based on parameters, like distance, delay, trust, and predicted energy. Figure 2 illustrates the structural view of the CWGO-routing protocol in WSN.

4.1 | Multiobjective model

In WSN, energy utilization can be significantly boosted by finding out the ideal CH and the ideal path for communication. This can be accomplished by regarding various constraints, like delay, intracluster distance, intercluster distance, and LLT while determining the CH and route. These parameters are explicated as follows.

a. Intracluster distance

The distance of the r^{th} node to the s^{th} CH in the cluster Z is termed as intra cluster distance, and generally a high value of intra cluster distance is deemed as ideal. The intracluster distance is determined as follows,

$$\delta_1 = \frac{1}{\beta_1 * m * n} \sum_{r=1}^{m} \sum_{\substack{s=1 \\ r \neq s}}^{n} l_{rs} \tag{7}$$

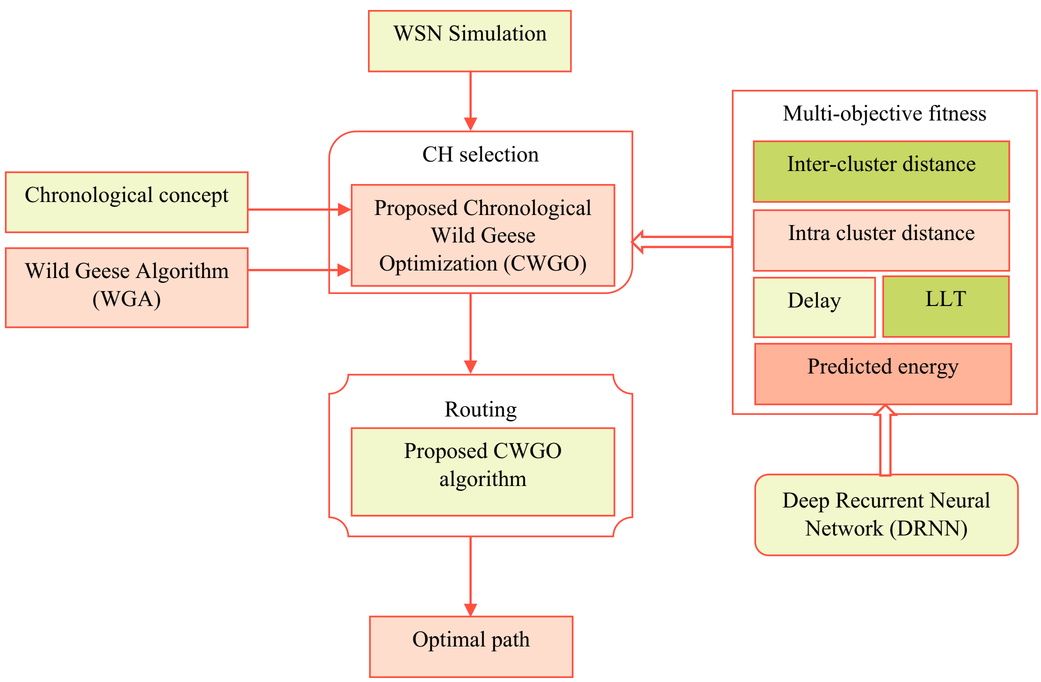

FIGURE 2 Structural view of the CWGO-routing technique in WSN.

where β_1 symbolizes the normalization constant, δ_1 indicates the intracluster distance, m and n denotes the node count and CH count, correspondingly.

b. Intercluster distance

This constraint refers to the distance between two CHs and the intercluster distance always has to be kept minimum for reliable communication. The ensuing expression is utilized to compute the intercluster distance.

$$\delta_2 = \frac{1}{\beta_2 * n} \sum_{s=1}^{n} \sum_{e=1}^{n} l_{se} \tag{8}$$

Here, β_2 refers to the normalizing factor and l_{se} is the distance between the s^{th} and e^{th} CHs.

c. Delay

Delay is used to determine the time taken for the data packet to reach the CH s from the node e, and is expressed as

$$\vartheta = \sum_{i=1}^{n} \frac{A_i}{m} \tag{9}$$

Here, A_i refers to the node count in the i^{th} CH, and ϑ indicates the delay.

d. Predicted energy

The amount of energy available at the nodes is predicted using the DRNN[34,36] and is done based on the residual energy of the nodes ξ_r. Energy prediction is vital as it provides clear portrait of the energy utilization of the nodes, thus allowing in the determination of a reliable communication path. DRNN is employed for predicting energy owing to its ability to learn the discriminative features in the input data and producing highly accurate results. Further, it is effective in providing response to window sizes of varied dimension, rather than a fixed-dimension as required by the CNN.

4.1.1 | Architecture of DRNN

The DRNN is developed based on the idea that human cognition depends on memory as well as the prior experiences. The DRNN is a DL network devised by incorporating recurrent neural network (RNN) with a deep neural network (DNN). The DRNN is kind of Elman network that encompasses multiple RNN layers linked hierarchically in the time direction. Unlike the conventional neural networks, the DRNN takes into account the previous output along with the current input to determine the output at any time instant. Here, the hidden layers are connected to the hidden layers at the prior time instant and thus, the DRNN is effectual handling sequential data, like written natural language, time series (sensor) data, or speech. The RNN has the capability of effectively managing the raw information and here, every hidden state is connected to the subsequent layer in the present time step and the same layer in the subsequent time step. The internal layer of the DRNN comprises an LSTM, and it also utilizes cross entropy as the error function and softmax as the activation function in the output layer. The DRNN generates an activity class, which is linked to the maximal element value of the output vector, when applied with an input. The architecture of the DRNN is illustrated in Figure 3.

Consider there are a total of G layers in the DRNN, and assume that the v^{th} layer be subjected with the input $A^{(v),w} = \left[A_1^{(v),w} A_2^{(v),w} \cdots A_o^{(v),w} \cdots A_O^{(v),w}\right]^T$, at time w and it generates an output $B^{(v),w} = \left[B_1^{(v),w} B_2^{(v),w} \cdots B_o^{(v),w} \cdots B_O^{(v),w}\right]^T$. Here, O indicates the number of units in the v^{th} layer and o is an arbitrary unit, where a unit refers to an element pair in the input-output vectors. Consider $C^w = B^{(1),w}$ in the input layer, $D^w = A^{(G),w}$, and $E^w = B^{(G),w}$ in the output layer and let j

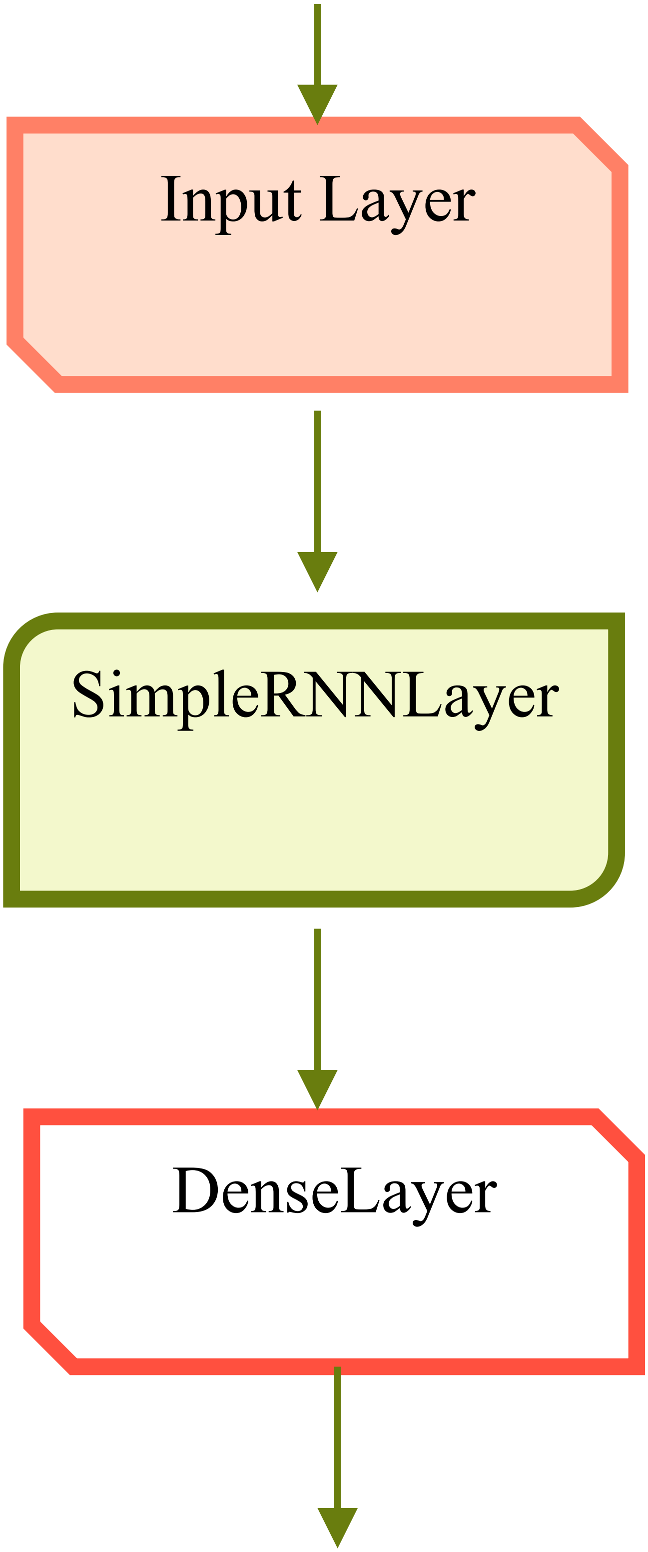

FIGURE 3 Architecture of DRNN.

and J represent the random and total units in the $(v-1)^{th}$ layer. $X^{(v)}\left(\in \mathfrak{R}^{O\times J}\right)$ specifies the input weight propagated to the v^{th} layer from the $(v-1)^{th}$ layer, and the recurrent weight is represented as $Q^{(v)}\left(\in \mathfrak{R}^{O\times J}\right)$. Then, the input vector $A_v^{(v),w}$ can be formulated as

$$A_v^{(v),w} = \sum_{j=1}^{J} x_{oj}^{(v)} B_j^{(v-1),w} + \sum_{o'}^{O} q_{oo''}^{(v)} B_{o'}^{(v),w-1} \tag{10}$$

Here, $x_{oj}^{(v)}$ and $q_{oo''}^{(v)}$ indicates the elements in $X^{(v)}$ and $Q^{(v)}$, and the output of the v^{th} layer is given by

$$B_o^{(v),w} = \eta^{(v)}\left(A_o^{(v),w}\right) \tag{11}$$

wherein the activation function is designated as $\eta^{(v)}$, and the output considering the bias and activation is given by

$$B^{(v),w} = \eta^{(v)}\left(X^{(v)}B^{(v-1),w} + Q^{(v)}B^{(v),w-1}\right) \tag{12}$$

The predicted energy is obtained by determining the overall output of the DRNN and is modeled as

$$\xi_p = \eta^{(G)}(D^w) = \eta^{(G)}\left(X^{(G)}B^{(G-1),w}\right) \tag{13}$$

Here, ξ_p refers to the energy predicted by the DRNN.

4.2 | CH selection

Clustering is one of the most commonly applied energy management features in WSN, and by clustering, the load at the BS is substantially minimized as the CH consolidates the information from every node in its cluster and communicates it to the BS. This helps in conserving the energy at the BS, as it obtains information from a limited number of nodes. The usage of CH minimizes the communication overhead and provides scalability. CH selection can be considered as an NP-hard issue and can be addressed by utilizing the CWGO approach. Here, the CWGO is the incorporation of the chronological concept with WGA.[35]

4.2.1 | Solution encoding

A cluster contains numerous nodes and it is essential to choose the ideal node as a CH to conserve energy. The CWGO algorithm proposed in this work is used to select the CH based on several constraints. The CWGO carries out multiple processes on the initial solution to determine the finest CH, and hence it is necessary to understand the manner in which the solutions are interpreted, and this is accomplished using solution encoding. The solutions of the CH selection problem are pictorially represented using the solution encoding portrayed in Figure 4.

4.2.2 | Fitness function

The finest CH is determined based on constraints, namely, LLT, delay, intracluster distance, predicted energy, and intercluster distance. In order to incorporate all these constraints, a multiobjective fitness function is framed as given below:

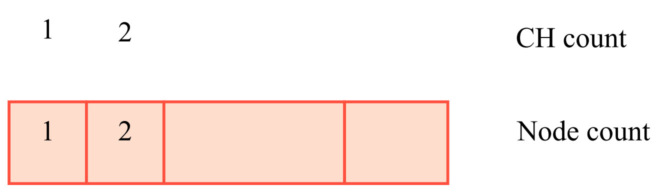

FIGURE 4 CH selection-solution encoding.

$$Fit_1 = \frac{1}{5}\left[\delta_1 + (1-\delta_2) + \left(1-\xi_p\right) + l + (1-LLT)\right] \tag{14}$$

Here, δ_1 terms the intracluster distance, which is computed using Equation (7), δ_2 designates the intercluster distance and it is determined with Equation (8), ξ_p is the energy predicted by the DRNN, l is the delay measured with Equation (9), and LLT is demonstrated in Section 3.2. A maximum value of fitness yields the finest CH.

4.2.3 | Proposed CWGO

The process of determining the finest CH is executed by using the CGWO technique, which is created by including the chronological concept in WGA.[35] The WGA is an algorithmic technique formulated on the swarm behavior of wild geese in the natural environment. The different characteristics of wild geese, like evolution, group migration, and casualty are considered while modeling the algorithm. The WGA is effective in solving high-dimension optimization issues with minimal computational complexity, and it is quite easy to implement. In WGA, the position of the individual is adapted depending on the information from its neighbors. Further, the realization of WGA is accomplished using multiple stages, like group migration, foraging, reproduction and evolution, death, migration, and ordered evolution. Despite these advantages, WGA has not been utilized for finding solutions in real time for large complex problems. By including the chronological concept, the convergence rate of the WGA can be further enhanced. The chronological concept is based on updating the solution based on its value at various time instants. The proposed CWGO is executed using the ensuing steps.

i. Initialization

The principal process in CGWO is to initiate the location of the group members randomly in the search space as represented in the following equation,

$$Y = \left\{Y_1, Y_2, .., Y_k, .., Y_{y_1}\right\} \tag{15}$$

Here, Y_k symbolizes the positional vector of the k^{th} wild goose and y_1 refers to the initial count of the wild geese. After creating the population, the personal best location H_k and migration velocity R_k are determined.

ii. Fitness computation

The next process is to sort the wild geese based on the objective, and for this, the fitness of each wild goose is computed using Equation (14). This sorting ensures that the wild geese to exploit data from the neighboring members.

iii. Harmonized migration

The population members travel in an ordered, coordinated, and controlled manner depending on the adjoining and upfront wild geese. Hence, the movement and velocity of the wild goose varies in coordination with the other members in the population and is given by

$$\begin{aligned} R_{k,z}^{e+1} = &\left(f_{1,z} \times R_{k,z}^{e} + f_{2,z} \times \left(R_{k+1,z}^{e} - R_{k-1,z}^{e}\right)\right) + f_{3,z} \times \left(H_{k,z}^{e} - Y_{k-1,z}^{e}\right) \\ &+ f_{4,z} \times \left(H_{k+1,z}^{e} - Y_{k,z}^{e}\right) + f_{5,z} \times \left(H_{k+2,z}^{e} - Y_{k+1,z}^{e}\right) - f_{6,z} \times \left(H_{k-1,z}^{e} - Y_{k+2,z}^{e}\right) \end{aligned} \tag{16}$$

wherein $H_{k,z}$, $R_{k,z}$, and $Y_{k,z}$ symbolizes the personal best, current velocity, and position of the k^{th} individual in the z^{th} dimension. $R_{k-1,z}^{e}$, and $R_{k+1,z}^{e}$ symbolizes the velocities of the rear and upfront wild geese, e indicates the current iteration, and $f_{i,z}, i = 1, 2, .., 11$ characterizes the arbitrary numbers homogeneously dispersed in $[0, 1]$.

Moreover, the movement of the population is guided based on the global best individual and the change in position is executed in a synchronized and well-organized manner depending on the upfront wild geese, which is given by

$$Y_{k,z}^{m} = H_{k,z}^{e} + f_{7,z} \times f_{8,z} \times \left(\left(N_{z}^{e} + H_{k+1,z}^{e} - 2 \times H_{k,z}^{e} \right) + R_{k,z}^{e+1} \right) \tag{17}$$

where $Y_{k,z}^{m}$ designates the position of the wild goose during migration and N_{z}^{e} designates the global best location in the population.

iv. Foraging

The location of the wild geese in this stage is modified in such a manner that the wild geese move toward the motion of the upfront member H_{k+1}^{e}. Here, the wild goose walks and searches for food and this behavior is modeled as follows:

$$Y_{k,z}^{ws} = H_{k,z}^{e} + f_{9,z} \times f_{10,z} \times \left(H_{k+1,z}^{e} - H_{k,z}^{e} \right) \tag{18}$$

Here, the position of the wild goose during walk and search is termed as $Y_{k,z}^{ws}$.

v. Reproduction and evolution

Reproduction and evolution is considered an alternative stage in the life cycle of the wild geese, and this is formulated by considering the previous two stages, namely, migration Y_{k}^{m} and foraging Y_{k}^{ws}, and this is modeled as

$$Y_{k,z}^{e+1} = \begin{cases} Y_{k,z}^{m} \quad if\, f_{11,z} \leq Cr \quad (a) \\ Y_{k,z}^{ws} \quad else \quad (b) \end{cases} \tag{19}$$

wherein Cr is assumed to have a value of 0.5, and when $f_{11,z} > Cr$, then

$$Y_{k,z}^{e+1} = Y_{k,z}^{ws} \tag{20}$$

Substituting Equation (18) in Equation (20),

$$Y_{k,z}^{e+1} = H_{k,z}^{e} + f_{9,z} \times f_{10,z} \times \left(H_{k+1,z}^{e} - H_{k,z}^{e} \right) \tag{21}$$

Subtracting $Y_{k,}^{e}$ on both sides of the above equation,

$$Y_{k,z}^{e+1} - Y_{k,z}^{e} = H_{k,z}^{e} + f_{9,z} \times f_{10,z} \times \left(H_{k+1,z}^{e} - H_{k,z}^{e} \right) - Y_{k,z}^{e} \tag{22}$$

At iteration e, the location of the k^{th} wild goose is obtained using Equation (21) as follows:

$$Y_{k,z}^{e} = H_{k,z}^{e-1} + f_{9,z} \times f_{10,z} \times \left(H_{k+1,z}^{e-1} - H_{k,z}^{e-1} \right) \tag{23}$$

Applying Equation (23) in the RHS of Equation (22),

$$Y_{k,z}^{e+1} - Y_{k,z}^{e} = H_{k,z}^{e} + f_{9,z} \times f_{10,z} \times \left(H_{k+1,z}^{e} - H_{k,z}^{e} \right) - \left(H_{k,z}^{e-1} + f_{9,z} \times f_{10,z} \times \left(H_{k+1,z}^{e-1} - H_{k,z}^{e-1} \right) \right) \tag{24}$$

$$Y_{k,z}^{e+1} = H_{k,z}^{e} + f_{9,z} \times f_{10,z} \times \left(H_{k+1,z}^{e} - H_{k,z}^{e}\right) - \left(H_{k,z}^{e-1} + f_{9,z} \times f_{10,z} \times \left(H_{k+1,z}^{e-1} - H_{k,z}^{e-1}\right)\right) + Y_{k,z}^{e} \tag{25}$$

$$Y_{k,z}^{e+1} = H_{k,z}^{e} - H_{k,z}^{e-1} + f_{9,z} \times f_{10,z} \times \left(H_{k+1,z}^{e} - H_{k,z}^{e} - H_{k+1,z}^{e-1} + H_{k,z}^{e-1}\right) + Y_{k,z}^{e} \tag{26}$$

The convergence rate of the WGA can be augmented by the utilization of the Chronological concept, and from the chronological concept,

$$Y_{k,z}^{e+1} = \frac{Y_{k,z}^{e+1} + Y_{k,z}^{e+1}}{2} \tag{27}$$

Applying Equation (21) and Equation (26) in the above equation,

$$Y_{k,z}^{e+1} = \frac{1}{2}\left[H_{k,z}^{e} + f_{9,z} \times f_{10,z} \times \left(H_{k+1,z}^{e} - H_{k,z}^{e}\right) + H_{k,z}^{e} - H_{k,z}^{e-1} + f_{9,z} \times f_{10,z} \times \left(H_{k+1,z}^{e} - H_{k,z}^{e} - H_{k+1,z}^{e-1} + H_{k,z}^{e-1}\right) + Y_{k,z}^{e}\right] \tag{28}$$

$$Y_{k,z}^{e+1} = \frac{1}{2}\left[2H_{k,z}^{e} + f_{9,z} \times f_{10,z} \times \left(H_{k+1,z}^{e} - H_{k,z}^{e} + H_{k+1,z}^{e} - H_{k,z}^{e} - H_{k+1,z}^{e-1} + H_{k,z}^{e-1}\right) - H_{k,z}^{e-1} + Y_{k,z}^{e}\right] \tag{29}$$

$$Y_{k,z}^{e+1} = \frac{1}{2}\left[2H_{k,z}^{e} + f_{9,z} \times f_{10,z} \times \left(2H_{k+1,z}^{e} - 2H_{k,z}^{e}2 - H_{k+1,z}^{e-1} + H_{k,z}^{e-1}\right) - H_{k,z}^{e-1} + Y_{k,z}^{e}\right] \tag{30}$$

The location of the wild geese is modified using the equation given above in the CWGO algorithm, where $Y_{k,z}^{e+1}$ represents the position of the k^{th} member in the z^{th} dimension at $(e+1)^{th}$ iteration.

vi. Demise, migration, and systematized evolution

In optimization algorithms, the population size and iteration count may not have an equal impact while solving various issues. In certain cases, the population size is found to be more effective than iteration count, and in other cases, iteration count is found to be best. Thus, to address this issue, a compromised solution is established. Here, the performance is balanced by utilizing a death phase for every function. In the initial stage, a total of y_1 wild geese are considered and as the iteration count increases, the worst wild goose is eradicated from the flock and the number of wild geese decreases in a linear manner thereby attaining a value of y_2 in the final iteration. The worst wild goose is removed based on the following equation:

$$y = round\left(y_1 - (y_1 - y_2) * \left(\frac{N}{N_{\max}}\right)\right) \tag{31}$$

Here, N refers to the evaluation function count and its highest value is represented as $N_{\max}$.

vii. Feasibility valuation

After the position of the wild geese is updated, the solution generated is examined for its feasibility by calculating the objective with Equation (14), and the solution with the minimal objective is regarded as the finest CH.

viii. Termination

The above steps are frequented till the stopping criteria is grasped and Algorithm demonstrates the pseudocode of the proposed CWGO.

Algorithm 1. Pseudocode of CWGO
Input: Initialize population y_1, $R_k^{e=1} = [0]$
Begin
Measure fitness with equation (14), and $N = y_1$
Identify personal best H_k and global best K for all geese
While $N \leq N_{\max}$
Sort the members from best to worst
For $k = 1 : y$
Pick the organized wild geese $e-1$, $e+1$, and $e+2$
For $z = 1 : W$
Estimate R_k^e with equation (16)
End for
For $z = 1 : W$
Determine $Y_{z,k}^m$ with equation (17)
End for
For $z = 1 : W$
Determine $Y_{z,k}^{ws}$ with equation (18)
End for
For $z = 1 : W$
Determine $Y_{z,k}^{e+1}$ with equation (19a) or equation (30)
End for
Check feasibility
End for
$N = N + y$
Estimate y with equation (31)
End while
end

The inclusion of the chronological concept in WGA significantly enhanced the convergence speed and increased the accuracy, and hence, effectively estimated the ideal CH for communication.

4.3 | Routing using the proposed CWGO

The finest path is determined from the multiple available paths using the CWGO technique based on delay, distance, predicted energy, and trust. Here, the CWGO is the novel optimization approach created by the inclusion of the chronological concept in WGA.[35]

4.3.1 | Solution encoding

The energy utilization in WSN can be significantly minimized by identifying the ideal route from the source to the destination. Here, the CWGO technique is applied to determine the finest path, and the initial set of solutions are operated upon by multiple processes, and so it is necessary to interpret the solution representation. This is represented by solution encoding and is displayed using Figure 5.

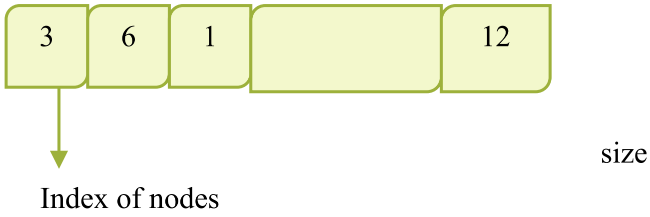

FIGURE 5 Solution encoding for routing.

4.3.2 | Fitness function

The ideal route is determined considering various constraints, like delay, distance, predicted energy and trust. In order to include all these constraints, a multiobjective fitness function is conceptualized as given below:

$$Fit_2 = \frac{1}{4}\left[\left(1-\xi_p\right)+(1-\zeta)+F+\vartheta\right] \tag{32}$$

Here, ξ_p refers to the predicted energy obtained by using the DRNN, ϑ is the delay, which is measured using Equation (9), F symbolizes the distance, and ζ denotes the trust and is expressed by

$$\zeta = \frac{1}{3}[DT+IT+ET] \tag{33}$$

where DT, IT, and ET refers to the direct, indirect, and error-based trust values and are briefed in Section 3.3.

Further, distance refers to the remoteness of the r^{th} node from the s^{th} CH and is formulated as

$$F = \|V_s - V_s\|\chi \tag{34}$$

Here, χ refers to the normalization constant.

4.3.3 | Proposed CWGO

Routing aims at finding the finest path available for communication from the multiple routes in such a way that it has a minimal delay and distance. Further, trust value has to be high to ensure reliability, and the nodes should have a high energy so as to improve the lifetime. Here, the ideal path is determined using the CWGO algorithm, which is developed by including the Chronological concept in WGA.[35] The proposed CWGO is detailed in Section 4.2.3. Although, the ideal path is identified based on the fitness depicted in Equation (32), the finest route should have a minimum objective.

5 | RESULTS AND DISCUSSION

The results obtained during the execution of the CWGO approach for CH selection and routing in this work are analyzed in this segment to reveal the superiority of the proposed technique. Further, the experimental set-up and metrics used are also exemplified.

5.1 | Experimental set-up

The experimentation of the CWGO approach for CH selection and routing is carried out on a PC using Python language.

5.2 | Simulation results

The simulation result obtained during the implementation of the CWGO in a WSN with 150 nodes when a total of 1000 rounds are considered is presented in Figure 6.

5.3 | Evaluation measures

Metrics, such as distance, delay, energy, and trust, are utilized in the evaluation of the CWGO approach and these measures are deliberated as follows.

i. *Delay*: This is measured with the help of Equation (9).
ii. *Distance*: Distance is computed using the expression (34).
iii. *Energy*: The energy parameter signifies the remnant energy of the nodes and is measured by calculating the difference between the initial energy and the energy consumed.

$$\xi_r = \xi_0 - \xi_{cons} \tag{35}$$

where ξ_r signifies the residual energy, ξ_0 indicates the initial energy, and ξ_{cons} denotes the consumed energy found with Equation (1) or Equation (2).

iv. *Trust*: Trust is determined with the help of Equation (33).

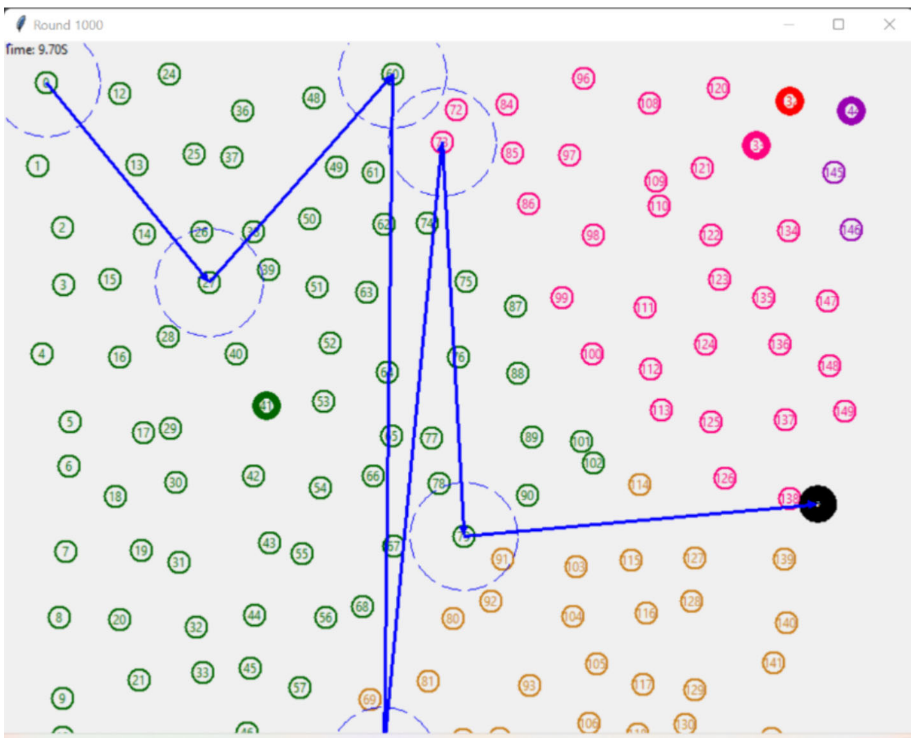

FIGURE 6 Simulation result of CWGO for a WSN with 150 nodes.

5.4 | Comparative techniques

The supremacy of the CWGO is investigated with respect to other approaches, such as EECHIGWO,[16] DUCISCA,[1] DE_SEP,[4] and E_CERP.[9]

5.5 | Comparative assessment

The analysis of the CGWO is done by considering WSN with 50, 100, 150, and 1000 nodes.

5.5.1 | Assessment with 50 nodes

In Figure 7, the examination of the CWGO for a WSN with 50 nodes with various evaluation metrics is depicted. Figure 7A demonstrates the assessment of the CWGO in terms of delay. With 500 rounds, the delay recorded by the various routing techniques, like EECHIGWO, DUCISCA, DE_SEP, E_CERP, and CWGO is 0.666, 0.609, 0.551, 0.415, and 0.363 s, respectively. Further, in Figure 7B, the evaluation of the CWGO in view of distance is portrayed. The CWGO measured a distance of 36.689 m, while the existing techniques required a higher distance of 55.743 m for EECHIGWO, 54.203 m for DUCISCA, 52.639 m for DE_SEP, and 42.189 m for E_CERP, with 500 rounds. The assessment of the CWGO considering energy is portrayed in Figure 7C. The CWGO recorded a higher energy value of 0.761 J for 500 rounds; however, the methods, such as EECHIGWO, DUCISCA, DE_SEP, and E_CERP, managed to achieve only a lower energy of 0.232, 0.357, 0.486, and 0.607 J, correspondingly. Likewise, the CWGO is analyzed for its supremacy considering trust and it is represented in Figure 7D. The trust attained by the available routing schemes, like

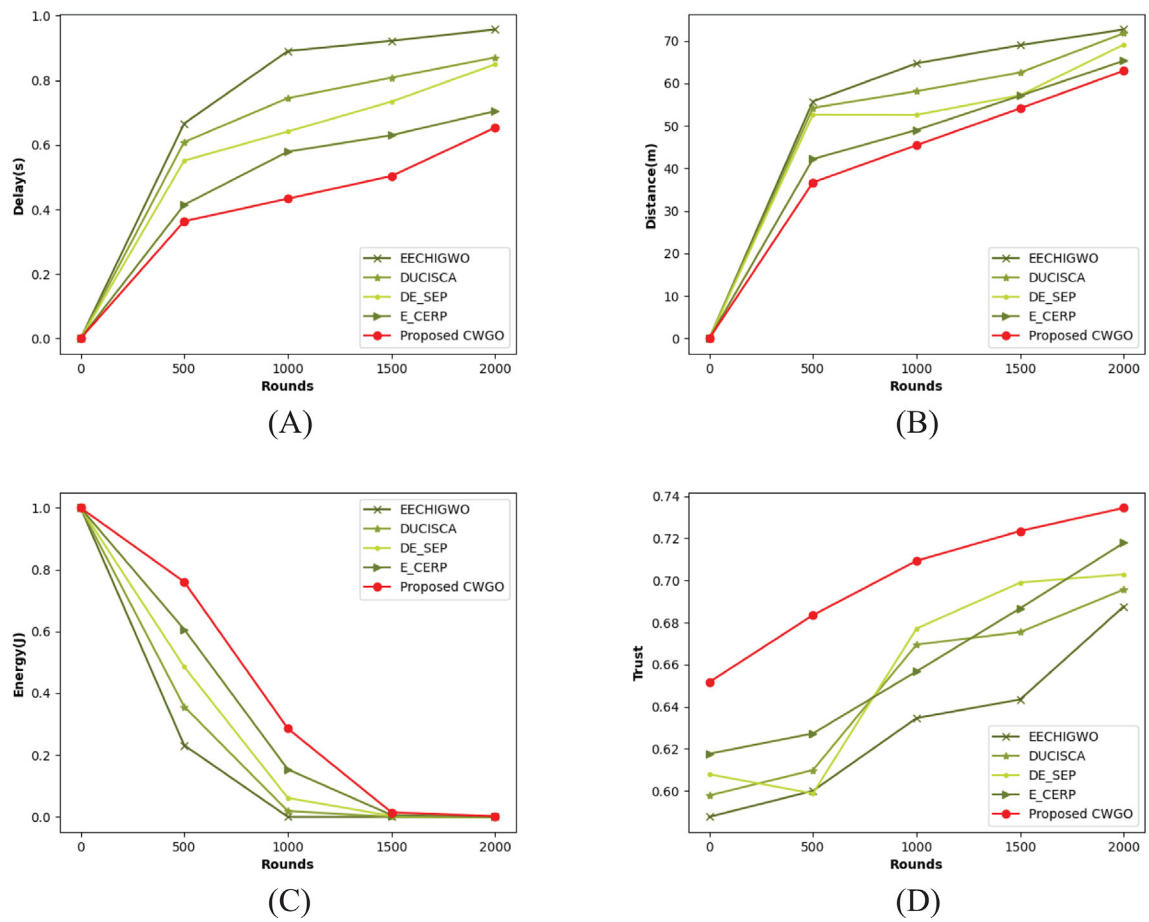

FIGURE 7 Analysis of the CWGO with a WSN having 50 nodes in terms of (A) delay, (B) distance, (C) energy, and (D) trust.

EECHIGWO is 0.600, DUCISCA is 0.610, DE_SEP is 0.599, and E_CERP is 0.627, with 500 rounds. A higher value of the trust at 0.683 is achieved by the CWGO, thus showing superior performance.

5.5.2 | Assessment considering 100 nodes

The comparison of the CWGO on the basis of various metrics with a WSN having 100 nodes is depicted in Figure 8. Figure 8A demonstrates the comparison of the CWGO with respect to delay. The techniques, like EECHIGWO, DUCISCA, DE_SEP, and E_CERP achieved a delay of 0.900, 0.756, 0.743, and 0.504 s, respectively, with 1000 rounds. But the proposed CWGO is found to realize a lower delay of 0.478 s, revealing its superiority. The examination of the based on distance is exhibited in Figure 8B. As compared to the existing methods, the CWGO realized a distance of 51.876 m, with 1000 rounds. But the value of distance achieved by the EECHIGWO is 159.297 m, DUCISCA is 127.961 m, DE_SEP is 104.294 m, and E_CERP is 53.875 m. Figure 8C displays the comparison of the CWGO considering the energy value. The residual energy attained by the methods, like EECHIGWO, DUCISCA, DE_SEP, E_CERP, and CWGO is 0.006, 0.198, 0.257, 0.498, and 0.569 J, respectively, with 1000 rounds and this implies that the CWGO has recorded a higher energy. Similarly, the trust-based comparison of the CWGO is explicated in Figure 8D. For 1000 rounds, the trust measured by the CWGO is 0.710, while a lower value of trust at 0.380, 0.537, 0.597, and 0.687 is attained by the prevailing methods, like EECHIGWO, DUCISCA, DE_SEP, and E_CERP.

5.5.3 | Assessment considering 150 nodes

The efficacy of the CWGO with a WSN of 150 nodes is examined based on various measures by considering different rounds and this is presented in Figure 9. The analysis of the CWGO concerning delay is exhibited in Figure 9A. With

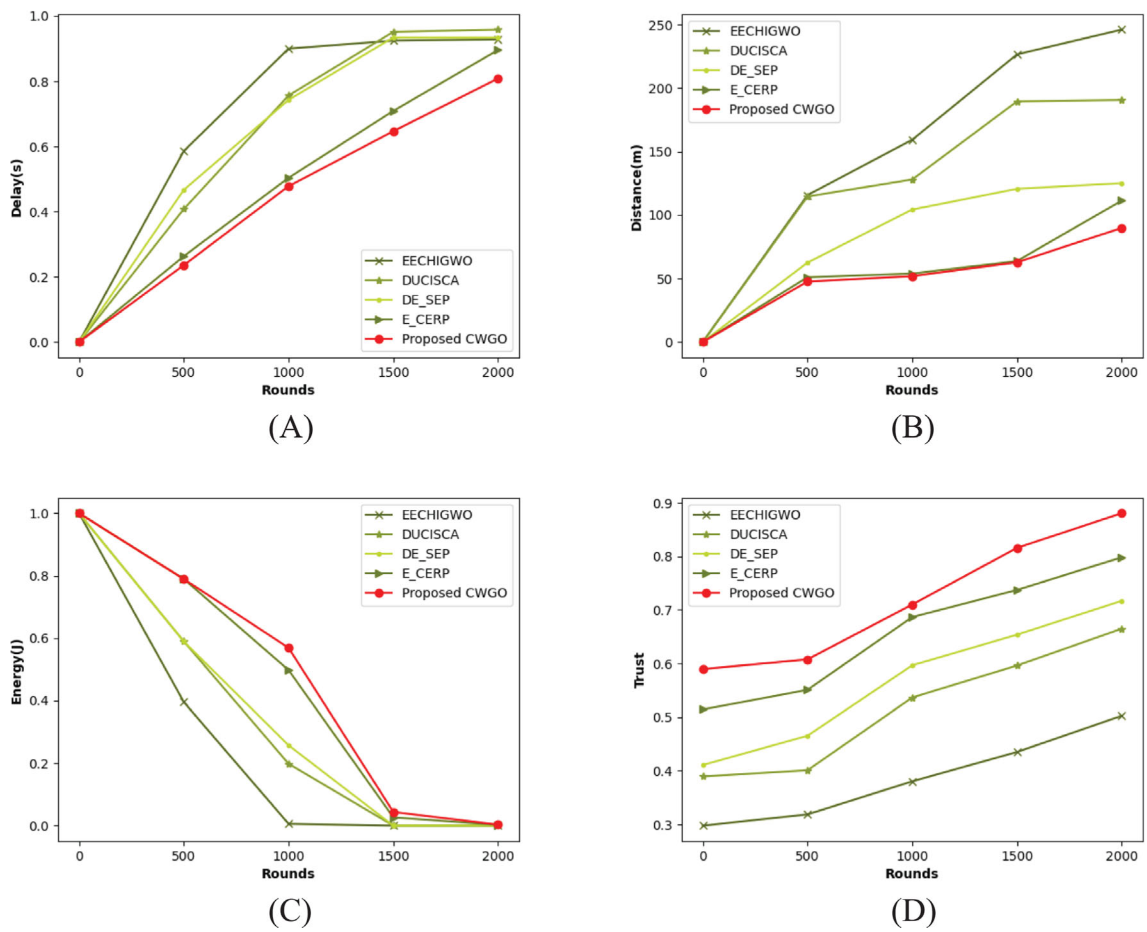

FIGURE 8 Assessment of the CWGO with a WSN having 100 nodes concerning (A) delay, (B) distance, (C) energy, and (D) trust.

1500 rounds, the delay computed by EECHIGWO is 0.925 s, DUCISCA is 0.859 s, DE_SEP is 0.825 s, E_CERP is 0.571 s, and CWGO is 0.519 s, which demonstrates that the CWGO required only a minimal time for transmission. The investigation of the CWGO concerning distance is characterized in Figure 9B. The CWGO computed a minimal distance of 55.766 m, with 1500 rounds but the distance figured by EECHIGWO, DUCISCA, DE_SEP, and E_CERP is 65.985, 72.599, 77.898, and 75.590 m, respectively. Figure 9C demonstrates the examination of CWGO on the basis of energy. The CWGO achieved a higher residual energy of 0.071 J, while the energy computed by the existing methods is 0.007 J for EECHIGWO, 0.020 J for DUCISCA, 0.019 J for DE_SEP, and 0.045 J for E_CERP. In Figure 9D, the investigation of the CWGO with respect to trust is exhibited. The trust achieved by EECHIGWO, DUCISCA, DE_SEP, E_CERP, and CWGO with 1500 rounds is 0.465, 0.606, 0.694, 0.767, and 0.806, respectively. This shows that the CWGO has managed to attain a high trust than the available routing schemes.

5.5.4 | Assessment considering 1000 nodes

Figure 10 shows the performance of the CWGO in WSN of 1000 nodes by changing the number of rounds. The analysis of the CWGO concerning delay is provided in Figure 10A. With 2000 rounds, the delay computed by EECHIGWO is 0.601 s, DUCISCA is 0.572 s, DE_SEP is 0.533 s, E_CERP is 0.502 s, and CWGO is 0.462 s. The analysis of the CWGO concerning distance is characterized in Figure 10B. When the number of rounds is 2000, the CWGO computed a distance of 20.453 m, on the other hand, the distance computed by the existing methods, such as EECHIGWO, DUCISCA, DE_SEP, and E_CERP is 50.557, 60.453, 65.664, and 40.541 m, respectively. Figure 10C shows the analysis of CWGO based on energy. When the number of round is 2000, the CWGO has a residual energy of 0.570 J, while the residual energy of the existing methods, such as EECHIGWO, DUCISCA, DE_SEP, and E_CERP is 0.408, 0.436, 0.493, and

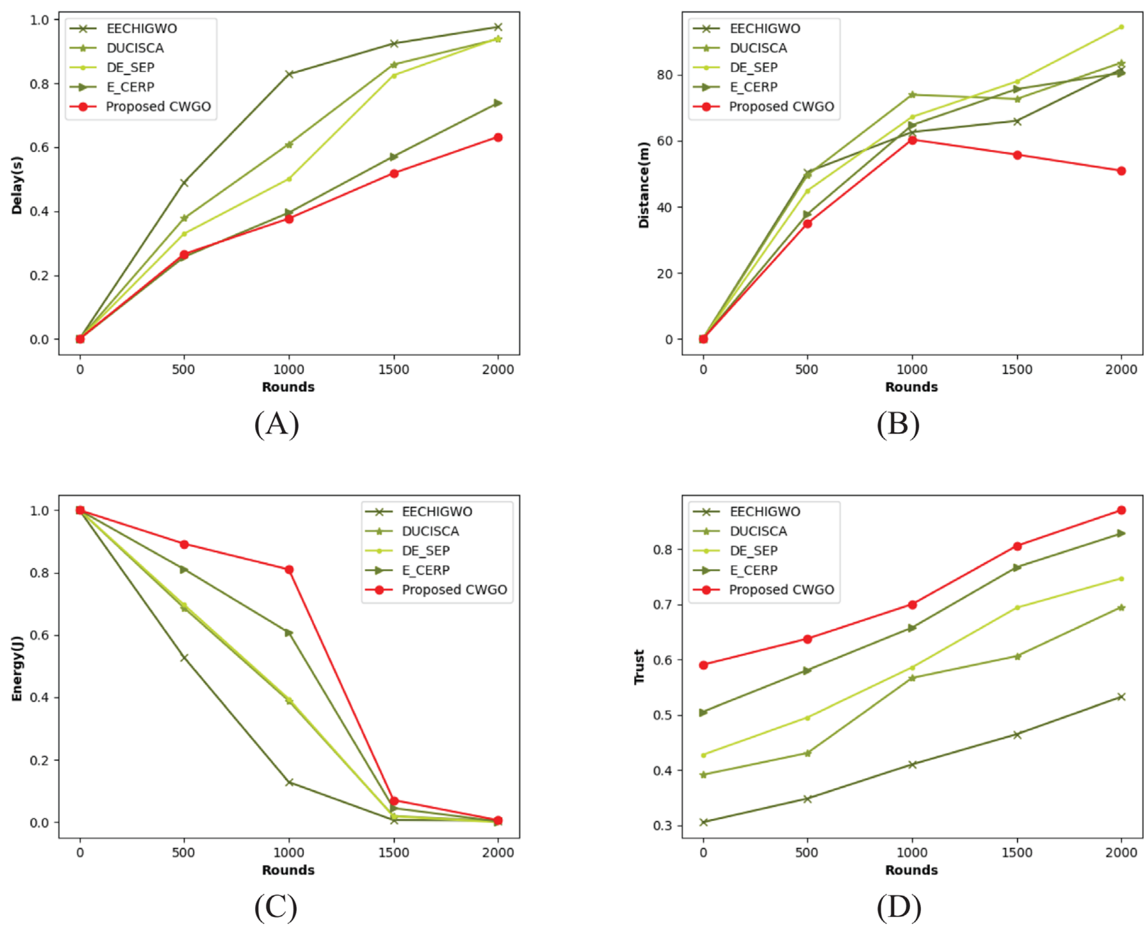

FIGURE 9 Examination of the CWGO with regard to WSN with 150 nodes considering (A) delay, (B) distance, (C) energy, and (D) trust.

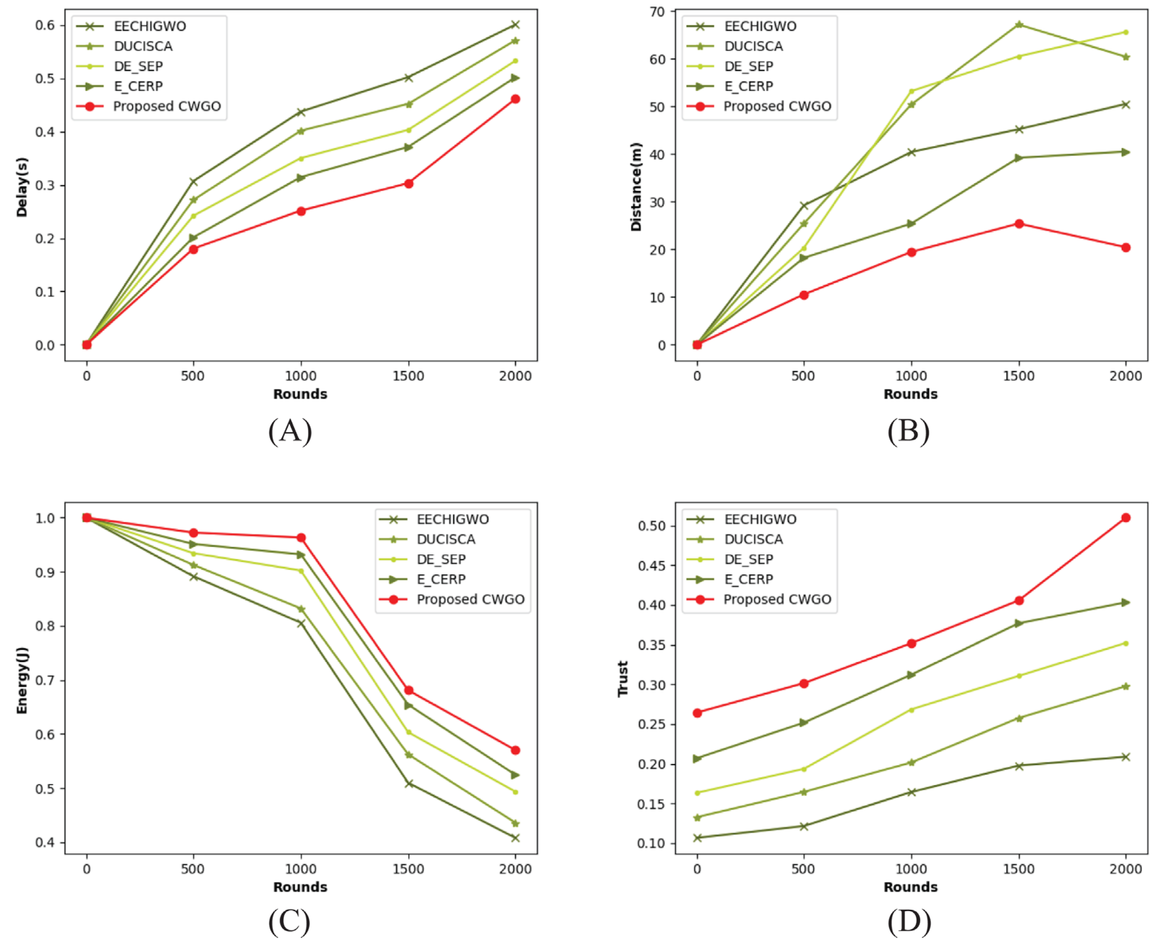

FIGURE 10 Examination of the CWGO with regard to WSN with 1000 nodes considering (A) delay, (B) distance, (C) energy, and (D) trust.

0.524 J, respectively. Figure 10D shows the performance of the CWGO in terms of trust. When the number of round is 2000, the trust achieved by EECHIGWO, DUCISCA, DE_SEP, E_CERP, and CWGO is 0.209, 0.298, 0.352, 0.403, and 0.510, respectively.

5.6 | Comparative discussion

The CWGO is analyzed for its superiority according to various metrics, like delay, distance, energy, and trust with respect to other routing schemes and this is demonstrated in Table 3. The analysis is accomplished considering a WSN with various number of nodes 50, 100, 150, and 1000, the values recorded in the table are attained with 1000 rounds. With 150 nodes, the proposed CWGO has attained a delay of 0.377 s, while the delay measured by EECHIGWO is 0.828 s, DUCISCA is 0.610 s, DE_SEP is 0.501 s, and E_CERP is 0.395 s. Further, the techniques, such as EECHIGWO, DUCISCA, DE_SEP, E_CERP, and CWGO, recorded distance values of 62.586, 73.875, 67.166, 64.696, and 60.312 m, respectively. Here, the CWGO is found to measure a low distance and delay value due to the application of CWGO for CH selection and routing leading to the determination of the shortest energy-efficient path. Likewise, the energy measured by EECHIGWO is 0.129 J, DUCISCA is 0.389 J, DE_SEP is 0.395 J, E_CERP is 0.608 J, and CWGO is 0.810 J. The global optimization ability of the CWGO lead to a balanced energy utilization among the different nodes, thus leading to a high residual energy. Similarly, the techniques, such as EECHIGWO, DUCISCA, DE_SEP, E_CERP, and CWGO recorded trust values of 0.410, 0.567, 0.586, 0.658, and 0.700. Here, the optimal paths are identified based on the direct, indirect and error-based trust values of the nodes, and so only the trustworthy nodes are used during communication, thus leading to high trust values.

TABLE 3 Comparative discussion of the CWGO.

Number of nodes	Metrics	EECHIGWO	DUCISCA	DE_SEP	E_CERP	Proposed CWGO
50	Delay (s)	0.891	0.745	0.641	0.579	0.433
	Distance (m)	64.691	58.147	52.582	49.015	45.455
	Energy (J)	0.000	0.019	0.061	0.154	0.286
	Trust	0.635	0.669	0.677	0.657	0.709
100	Delay (s)	0.900	0.756	0.743	0.504	0.478
	Distance (m)	159.297	127.961	104.294	53.875	51.876
	Energy (J)	0.006	0.198	0.257	0.498	0.569
	Trust	0.380	0.537	0.597	0.687	0.710
150	Delay (s)	0.828	0.610	0.501	0.395	**0.377**
	Distance (m)	62.586	73.875	67.166	64.696	**60.312**
	Energy (J)	0.129	0.389	0.395	0.608	**0.810**
	Trust	0.410	0.567	0.586	0.658	**0.700**
1000	Delay (s)	0.438	0.402	0.350	0.315	0.252
	Distance (m)	40.454	50.434	53.245	25.433	19.468
	Energy (J)	0.806	0.832	0.902	0.932	0.963
	Trust	0.164	0.202	0.268	0.312	0.352

TABLE 4 Running time.

Methods	Running time (seconds)
EECHIGWO	25.986
DUCISCA	20.632
DE-SEP	18.554
E-CERP	16.215
Proposed CWGO	13.548

Below are some of the factors that contribute to the developed approach's superior performance:

Energy prediction is vital as it provides clear portrait of the energy utilization of the nodes, thus allowing in the determination of a reliable communication path. DRNN is employed for predicting energy owing to its ability to learn the discriminative features in the input data and producing highly accurate results. Further, it is effective in providing response to window sizes of varied dimension, rather than a fixed-dimension as required by the CNN. The usage of CH minimizes the communication overhead and provides scalability. The CWGO algorithm proposed in this work is used to select the CH based on several constraints. The CWGO algorithm is created by including the chronological concept in WGA. The WGA is effective in solving high-dimension optimization issues with minimal computational complexity, and it is quite easy to implement. By including the chronological concept, the convergence rate of the WGA can be further enhanced. The chronological concept is based on updating the solution based on its value at various time instants. By combining the advantages of the chosen methods, the performance of the proposed method is better.

5.7 | Running time

Table 4 shows the running time of the proposed and existing methods. The running time of the proposed method is 13.548 s, whereas the running time of the existing methods, such as EECHIGWO, DUCISCA, DE-SEP, and E-CERP is 25.986, 20.632, 18.554, and 16.215 s, respectively.

6 | CONCLUSION

An innovative energy-aware routing protocol is presented in this work for increasing the lifespan as well as the energy efficiency of WSN. At first, the DRNN is used to predict the available energy of the nodes, and then the finest CH is selected by the CGWO algorithm based on energy, delay, LLT, intercluster and intracluster distances. Further, in order to accomplish data transmission, the ideal path from the node to the BS has to be discovered, and this is accomplished by the CWGO based on constraints, like trust, delay, distance, and energy. The CWGO proposed in this work is the hybridization of the Chronological concept in WGA. Moreover, the superiority of the CWGO is scrutinized in terms of trust, distance, delay, and energy and is observed to produce a low delay of 0.252 s and a distance of 19.468 m, along with high energy of 0.963 J and trust of 0.700. The advantages of the proposed method are enhanced convergence speed and increased accuracy; also, it is useful in enhancing the lifetime, reliability, minimizing delay of WSN, and so on.

DATA AVAILABILITY STATEMENT

No new data were generated or analyzed in support of this research.

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