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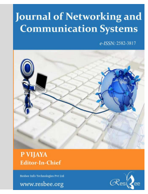

Multihop Routing Using Chaotic Salp Swarm Optimization Algorithm in WSN

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Abstract: In order to set up communication among the IoT devices, the Wireless Sensor Network (WSN) plays a significant role. In WSN, routing is considered a significant research topic, because it aids to find the appropriate paths for communication. The main aim of this work is to present a multipath routing approach on the basis of the optimization approach. Here, the adopted routing approach possesses two significant tasks as multipath routing and Cluster Head Selection (CHS). At first, the kernel-based Fuzzy C means (FCM) method is exploited to select the CH. Subsequently, the novel Chaotic Salp Swarm Optimization (C-SSO) algorithm is developed for multipath routing. Here, numerous constraints like energy trust and QoS are considered to design the fitness function of the developed method. The experimentation of the developed method is performed by exploiting diverse WSN setups and the outcomes are evaluated by numerous comparative approaches. It is clearly evident from the outcomes that the adopted model on the basis of the multipath routing has superior performance in terms of energy, delay, throughput, and number of alive nodes respectively.

Keywords: WSN, CHS, multipath, routing, energy, trust

Nomenclature

Abbreviation	Description
PSO	Particle Swarm Optimization
MOFPL	Multi-objective fractional particle lion algorithm
SCH	SuperCluster Head
GA	Genetic Algorithm
WSN	Wireless Sensor Networks
BOA	Butterfly Optimization Algorithm
ACO	Ant Colony Optimization
IoT	Internet of Things
DMEERP	Dynamic Multi-hop Energy Efficient Routing Protocol
BS	Base Station
Taylor C-SSA	Taylor based Cat Salp Swarm Algorithm
LEACH	Low Energy Adaptive Clustering Hierarchy

1. Introduction

WSNs indicate as an important assist platform for the urgent situation and pervasive computing areas. The integration of both data communication and data sensing is considered the main development in the WSNs. The WSN was mainly deployed for various applications like detection of threat and object monitoring and tracking of the environment etc. Generally, the WSN comprises numerous number of sensor nodes that are positioned statically by means of minimum processing, energy, and communicated by means of the diminutive range radio links. In that case, to form a network, in an ad hoc manner the sensor nodes are positioned with transitional nodes. In addition, to transfer the data, single-hop communication was developed because of the restricted range of communication.

In WSN, energy efficiency is considered an important issue, as sensor nodes are set off by exploiting the battery. Hence, to prolong the lifetime of the network the utilization of energy is vital. In WSN, the sensor nodes have two roles: (a) from the physical environment the data is accumulated, (b) the data collection process is performed from WSN to perform the data routing to the neighbor node. In a large-scale network, the multihop is considered as the general model to transmit data to BS. When starting

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communication, energy is considered an important issue. Hence, to provide an efficient routing the number of transmissions is reduced in order to extend the lifetime of the network.

In WSN, routing protocols are classified as single and multipath routing protocols. Moreover, through the intermediate nodes, from a sender node to receiver node, nodes deliver the packet in WSN. Based on load balancing and the energy efficiency of the network, through multiple hops, the packet is delivered to the base station in WSN. Moreover, for effectual routing, routing protocols attempt to discover tradeoff among the cost of the energy, delay, and load balancing factors in WSN. In WSN, the nodes are battery-powered; also sensor node batteries are very expensive. Therefore, routing protocols must offer maximized throughput by means of effectual minimization in the end-to-end delay of the network. To reach the base station from the source node, the single path routing protocols are analyzed paths. Hence, it chooses only a single path for routing. However, the main drawback of the single path routing is it affects when the environment possesses a large number of noise factors. Conversely, the probable paths are analyzed by the multipath routing and also choose more than one path for the routing in WSN. The network load has effectively been handled by multipath routing protocols because the routing path availability is high. Moreover, it raises the reliability and bandwidth of the WSN [9].

To extend the sensor network lifetime, optimization techniques were utilized for energy-aware routing protocols. Nowadays, numerous optimization issues, like wireless sensor network routing was studied by most researchers. In addition, other optimization techniques, namely PSO and GA, were exploited for multi-path routing. Hence, the main intention of this paper is to adopt a Chaotic Salp Swarm Optimization Algorithm (C-SSO) for the multipath routing technique in WSN. Here, the optimal selection of the path does not affect any local minimal trap issue.

2. Literature Survey

In 2020, Prachi Maheshwari Dr et al [1], worked on the WSN in order to reduce the energy utilization and to improve the lifetime of the network. Here, to choose an optimal CH from a cluster of nodes BOA was exploited. Moreover, the ACO was used to recognize the route between CH and BS. On the basis of the remaining energy, distance, and degree of the nodes, the ACO chooses the optimal route. Finally, the proposed method performance metrics were validated by using the dead nodes, energy utilization, alive nodes and the data packets obtained by the Base station.

In 2020, V. Nivedhitha et al [2], presented a DMEERP to balance the ratio of path reliability and energy utilization. Initially, basic presumption, and network model, was performed for cluster formation and multihop route connection. The records of all cluster members and CH have been saved and maintained by the SCH. If the existing CH was not up to snuff, the weight factor and activation of the node were calculated in order to attain the novel CH. Next, the ratio of the path reliability was calculated for the packet routing without losing a large amount of packet. Finally, on the basis of the channel capacity model, the energy model was implemented.

In 2019, A. Vinitha et al [3], addressed the energy problem in WSN and offers an energy effectual multi-hop routing. The method is called Taylor C-SSA it is modified by C-SSA with Taylor series. The developed technique experiences two schemes to attain the multihop routing such as CHS and data transmission. Initially, the LEACH protocol was exploited for the energy effectual CHS and also for the transmission of the data. Finally, the chosen optimal hop selection was performed by adopted Taylor C-SSA.

In 2019, Reeta Bhardwaj and Dinesh Kumar [4], adopted multi-objective fitness functions based on energy, delay, cluster density, and distance. The developed MOFPL was exploited for energy-aware routing. From several CH nodes to discover the optimal CH the developed MOFPL approach was utilized in the WSN. Subsequently, the developed multiobjective function was utilized for the optimal routing path.

In 2019, Ramin Yarinezhad and Seyed Naser Hashemi [5], developed an approximation method by means of an approximation ratio of 1.1. Moreover, this approach runs in fixed-parameter well-mannered time. In addition, a routing approach on the basis of the aforesaid structure was proposed. To find the appropriate paths among each CH and the BS the routing approach minimizes and balances the energy utilization in the network.

In 2020, Amit Singh and A. Nagaraju [6], developed an application of two diverse approaches in order to enhance the sensor network performance regarding the placement of the base station besides with the construction of the route and the optimization approach exploiting nature-inspired calculation techniques. Moreover, to minimize the number of transmissions opportunistic coding was used at potential relays. Therefore, the developed implementation combines three approaches that combine the advantages of every important improvement in the transmission of the data.

3. C-SSO Algorithm for Multihop Routing in WSN

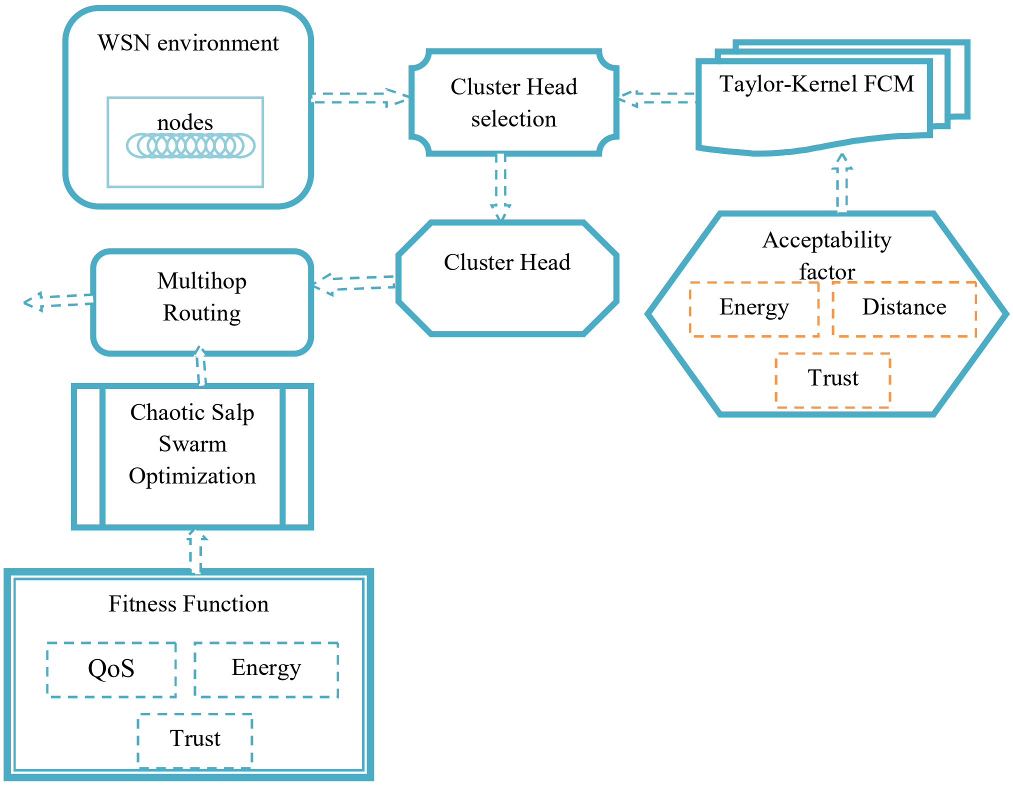

Fig. 1. *Architecture model of the adopted approach in multihop routing*

The adopted technique attempts to choose the optimal multipath for the routing as shown in Fig. 1. By means of wireless connection, the WSN is connected which possesses numerous nodes that are positioned all over the simulation area. Here, several paths and intermediary nodes are considered hence, the source, and the destination, can communicate with each other. In the WSN, the sensor node possesses energy constraint, because it needs to recognize the 'm' optimal multipaths from k paths. Therefore, the adopted model performs two important tasks such as CHS and multipath routing. The Taylor kernel FCM scheme is utilized for the optimal CHS and the distance, energy, and trust is used to derive the acceptability factor. Moreover, to choose the optimal paths a multipath routing approach is performed and it is chosen by Taylor-based kernel FCM. Then, the optimization algorithm is adopted named C-SSO algorithm and it is based upon the fitness model and is derived based on energy, QoS, and trust. At last, to identify the optimal multipath the adopted model is used for the WSN communication.

3.1Taylor Kernel Fuzzy C-Means Clustering Technique: CHS

The path selection process is performed for an appropriate CH for the routing in starting stage of the adopted multipath routing. In the WSN, the source and destination nodes are divided by a huge count of nodes. In addition, the cluster head selection is very necessary, hence; via the CH the routing path can be set up.

On the basis of the acceptability factor, the optimal CH is selected by the Taylor kernel FCM for the WSN routing. Moreover, the acceptability factor consists of 2 restraints such as energy, distance, and trust. In order to derive the acceptability factor, the cluster head is very important with maximum energy and trust and the minimum distance for communication, and these three constraints are multiplied by three constants as α , β , and γ

The formulation of Taylor kernel FCM for acceptability factor is stated as below:

$$F = \alpha . E + \beta . D + \gamma . T \tag{1}$$

In eq. (1), D , E , and T indicates the distance, energy, and node trust. Conversely, α , β , and γ indicates the equalization constraints, and its summation is equivalent to unity. In acceptability factor each term is stated as below:

Energy:

Let WSN comprises Q number of CHs, and E_q indicates computation of energy residual on each CH. The network energy is indicated as,

$$E = \sum_{q=1}^{Q} E_q \tag{2}$$

In eq. (2), E_q denotes the energy of q^{th} CH in WSN and Q denotes the total CHs considered for WSN.

Distance:
Distance is considered one of the important constraints for communication, it is measures distance among q^{th} cluster and its s^{th} neighbor node. Consider WSN has S neighboring nodes, therefore, the distance measure is stated as,

$$D = \frac{1}{Q*S} \sum_{q=1}^{Q} \sum_{\substack{s=1 \\ q \in s}}^{S} \frac{D_{qs}}{N_F} \tag{3}$$

Whereas, D_{qs} signifies distance among q^{th} CH and s^{th} neighboring nodes. The variables N_F and S denotes the total number of normalization factors and neighboring nodes.

Trust:
On the basis of the CH node communication, the trust depends, which must be maximum as probable. By means of the communication performed among 2 nodes, the trust is computed and it is stated as below:

$$T = \frac{1}{Q*S} \sum_{q=1}^{Q} \sum_{\substack{s=1 \\ q \in s}}^{S} T_{qs} \tag{4}$$

In eq. (4), T_{qs} indicates the trust measured among the q^{th} CH and the s^{th} neighboring node. The network trust directly based upon 3 factors, like recent, direct, and indirect trusts, and it is stated as,

$$T_{qs} = \frac{T^{direct} + T^{indirect} + T^{recent}}{3} \tag{5}$$

In interval [0,1] the trust value of the node is dependent, here 1 states the trusted node, and 0 stated the no trust. Eq. (5) indicates the trust factors and it is calculated as below:

Direct trust: It is calculated by the total packets transmitted and received by a node, and it is calculated as,

$$T^{direct}(t) = \frac{P_{qs}(t)}{R_{qs}(t)} \tag{6}$$

whereas, $P_{qs}(t)$ and $R_{qs}(t)$ indicates packets received and sent among the q^{th} and s^{th} node at the time of communication during the time t.

Indirect trust: It is calculated on basis of the direct trust calculated from the target node and it is computed as below:

$$T^{indirect}(t) = \frac{1}{g} \sum_{u=1}^{U} T_{u,s}^{direct}(t) \tag{7}$$

u states the neighboring node of s^{th} node and it deviates in the range of $1 \le u \le U$.

Recent trust: It is calculated from the direct trust and the indirect trust, and value-based upon target node behavior.

$$T^{recent}(t) = \mu * T^{direct}(t) + (1-\mu) * T^{indirect}(t) \tag{8}$$

μ states the direct trust weight, and it is stated the value as 0.5.

3.2 Taylor Kernel FCM Algorithm

For the Taylor kernel FCM, acceptability factor is modeled, the technique chooses the appropriate CHs between the several nodes on the basis of the subsequent steps:

a) Initialization: In this step, this approach arbitrarily selects A clusters from WSN, and cluster centre is stated as A_i $(1 \le i \le I)$. Moreover, A_i denotes the i^{th} cluster center and I indicates the total cluster centres in WSN. The clustering task is performed by Taylor kernel FCM techniques on the basis of the fuzzy logic and a kernel parameter κ.

b) Calculate the membership matrix: A membership function is derived for the clustering, and it is stated as,

$$M_{bi}=\frac{\left(\frac{1}{1-\kappa(\omega_b,A_i)}\right)^{\frac{1}{v-1}}}{\sum_{i=1}^{i}\left(\frac{1}{1-\kappa(\omega_b,A_i)}\right)^{\frac{1}{v-1}}} \tag{9}$$

M_{bi} states the membership degree of the data point, and kernel function, is stated as $\kappa(\omega_b,A_i)$. Based on the data point ω_b and the cluster center A_i kernel function is measured. Moreover, a hyperbolic tangential function is utilized and it is stated as,

$$\kappa(\omega_b,A_i)=1-\tanh\left(\frac{-|\omega-A|^2}{i^2}\right) \tag{10}$$

In the Taylor series, the hyperbolic tangential function is applied to enhance the strength of clustering.

Update cluster centers: After the update of the membership degree, the cluster centers are updated and it is stated as below:

$$A_i(t+1)=\frac{\sum_{b=1}^{d}M_{bi}^{v}\,\kappa(\omega_b,A_i).\,\omega_b}{\sum_{b=1}^{d}M_{bi}^{v}\,\kappa(\omega_b,A_i)} \tag{11}$$

The conventional KFCM clustering approach is used for the updating of the cluster center and which is stated in eq. (11) and it is enhanced by the Taylor series which is described as follows. The Taylor series [7] is stated as,

$$\begin{aligned}A_i(t+1)&=0.5A_i(t)+1.3591A_i(t-1)-1.359A_i(t-2)+0.6795A_i(t-3)-0.2259A_i(t-4)+\\&\quad 0.055A_i(t-5)-0.0104A_i(t-6)+1.38e^{-5}A_i(t-7)-9.92e^{-5}A_i(t-8)\end{aligned} \tag{12}$$

$$A_i(t)=\frac{1}{0.5}\left\{\begin{aligned}&A_i(t+1)-1.3591A_i(t-1)+1.359A_i(t-2)-0.6795A_i(t-3)+0.2259A_i(t-4)-\\&0.055A_i(t-5)+0.0104A_i(t-6)-1.38e^{-5}A_i(t-7)+9.92e^{-5}A_i(t-8)\end{aligned}\right\} \tag{13}$$

For adjustment, initially, eq. (11) is adjusted by subtracting variables $A_i(t)$ on both sides as in eq. (14).

$$A_i(t+1)-A_i(t)=\frac{\sum_{b=1}^{d}M_{bi}^{v}\,\kappa(\omega_b,A_i).\,\omega_b}{\sum_{b=1}^{d}M_{bi}^{v}\,\kappa(\omega_b,A_i)}-A_i(t) \tag{14}$$

Substituting eq. (13) in eq. (14),

$$A_i(t+1)-\frac{1}{0.5}\left\{\begin{aligned}&A_i(t+1)-1.3591A_i(t-1)+1.359A_i(t-2)-\\&0.6795A_i(t-3)+0.2259A_i(t-4)-\\&0.055A_i(t-5)+0.0104A_i(t-6)-\\&1.38e^{-5}A_i(t-7)+9.92e^{-5}A_i(t-8)\end{aligned}\right\}=\frac{\sum_{b=1}^{d}M_{bi}^{v}\,\kappa(\omega_b,A_i).\,\omega_b}{\sum_{b=1}^{d}M_{bi}^{v}\,\kappa(\omega_b,A_i)}-A_i(t) \tag{15}$$

$$A_i(t+1)=A_i(t)+\left\{\begin{aligned}&2.7182\ A_i(t-1)-2.7182\ A_i(t-2)+\\&1.359\,A_i(t-3)-0.4518\ A_i(t-4)+\\&0.11\,A_i(t-5)-0.0208\ A_i(t-6)+\\&2.76\ e^{-3}A_i(t-7)-19.84\ e^{-5}A_i(t-8)\end{aligned}\right\}-\frac{\sum_{b=1}^{d}M_{bi}^{v}\,\kappa(\omega_b,A_i).\,\omega_b}{\sum_{b=1}^{d}M_{bi}^{v}\,\kappa(\omega_b,A_i)} \tag{16}$$

By exploiting the Taylor series the modification of cluster center is happening which involves the cluster center of the preceding iteration for the calculation of the cluster center at the present iteration.

d) Checking the halt criteria: If the halting criteria are reached, the cluster centers are retaining to indicate the ultimate solution, or else, the iteration is recurring from step b. The halt criteria are stated as,

$$\vartheta=\max\left|z^{t+1}-z^{t}\right| \tag{17}$$

whereas z states the membership matrix, that is $z=[M_{bi}]$. When ϑ exceeds κ, resume step b or otherwise leap to step e.

e) On the basis of the acceptability factor optimal cluster center is selected: The cluster centers are given to the assessment of acceptability factor individually and cluster center with utmost acceptability factor is stated as optimal cluster center. On the basis of the eq. (1), the acceptability factor is calculated.

f) Terminate: The optimal cluster center A_{best} stated as the optimal solution. By exploiting the developed Taylor KFCM, the clustering overcomes the disadvantages related to the conventional KFCM.

In WSN, multiple routes are formed among the source and the destination subsequent to finding the appropriate CH nodes. Moreover, the C-SSO is used to derive the fitness factor by choosing the multiple paths between the several paths.

3.3 Fitness Model of Proposed Method

As the C-SSA approach chooses m multipaths among the k paths among sender and receiver, it is vital to state selection criterion for the path selection.

$$Fit = \frac{1}{3}\{QoS + E + T\} \tag{18}$$

whereas, QoS, E, and T indicates the QoS, energy and trust of multipath. The values of QoS, energy, and trust are indicated as below,

$$QoS = \frac{1}{m}\sum_{p=1}^{m-1}\left(D_{p,p+1} + S_{p,p+1}\right) * 1/2 \tag{19}$$

$$E = \frac{1}{m}\sum_{p=1}^{m-1}\left(E_p\right) \tag{20}$$

$$T = \frac{1}{m}\sum_{p=1}^{m-1}\left(T_{p,p+1}\right) \tag{21}$$

4. Proposed CSSO Algorithm

In the proposed CSSO algorithm [8], if the fitness value does not alter considerably for five successive times (the number of alter is less than 0.0001), hence Kent chaotic the map is introduced in this work which is to aid the proposed technique to jump out of local optimum. The Kent chaotic map is carried out as follows:

$$z_{t+1} = \begin{cases} Z_t / a, 0 < Z_t \le a \\ (1 - Z_t)/(1 - a), a < Z_t < 1 \end{cases} \tag{22}$$

a) If the value of the fitness does not alter considerably for five successive times. The present optimal the solution X_i is mapped to Kent equation domain [0,1] by exploiting the eq. (23) in order to attain the initial chaotic series of the chaotic series Z_0 .

$$Z_0 = \frac{X_i - X_{min}}{X_{max} - X_{min}} \tag{23}$$

b) Eq. (22) is used to produce a chaotic series and to attain a chaotic series $Z_k (k = 1,2,.....,n)$ with n chaotic variables.

c) To increase Z_k a carrier operation is performed, subsequently, load it onto individual X_i to be searched by exploiting eq. (24) to attain a new individual location U_k in the domain of unique solution space subsequent to chaotic operator operation, whereas $k = 1,2,.....n$.

$$U_k = X_i + \frac{(X_{max} - X_{min})}{2} * (2Z_k - 1) \tag{24}$$

Step 4: The fitness value $f(U_k)$ of U_k is computed and evaluated with fitness value of $f(X_i)$, and the improved solution is maintained.

In the proposed approach, the movement of the leaders is entirely followed by the followers. However, the movement of the leaders is entirely random. The fitness value of the subsequent moment location with the present location fitness value of the leader is doesn't compared while carrying out the position update, and it is simple to move to a poorer location.

An adaptive following scheme is developed to enhance the blind follow-up follower's behavior. At the time (i-1) and (j) the fitness is computed and also evaluated and the position is updated by exploiting the eq. (25).

$$x_j^i = \begin{cases} x_j^i + c_4\left(x_j^{i-1} - x_j^i\right), f\left(x_j^{i-1}\right) < f\left(x_j^i\right) \\ x_j^i + c_4\left(x_j^{i-1} - x_j^i\right), f\left(x_j^{i-1}\right) \ge f\left(x_j^i\right) \end{cases} \tag{25}$$

whereas, c_4 indicates an adaptive parameter, to regulate global and local search. Subsequent to the repeated comparison experiments, better outcomes are achieved by choosing $c_4 = 20/(1 + 0.01 * t)$

The basic initiative of Opposition-Based Learning (OBL) is the present solution, and it computes its opposite solution and fitness value of present and the opposite solution, and maintain a superior solution.

For the current solution x_i, the opposition solution is computed as $x_j = a_j + b_j - x_i$. Compute the fitness $f(x_i)$ and $f(x_j)$ of x_i and x_j correspondingly, and maintain the solution with superior fitness. In the conventional SSA approach, formerly the solution value goes beyond the boundary; the solution is directly set to the boundary value. This procedure is defined as eq. (26)

$$x_i = \begin{cases} ub & x > ub_i \\ lb & x_i < lb \\ x_i & \text{others} \end{cases} \tag{26}$$

Whereas ub and lb indicates the upper and lower bounds, correspondingly. Here, the following strategy as eq. (27) is used to optimize the boundary processing procedure

$$x_i = \begin{cases} lb + (ub - lb) \times rand(0,1) & x_i > ub, x_i < lb_i \\ x_i & \text{others} \end{cases} \tag{27}$$

Whereas $rand(0,1)$ indicates a random number following the standard normal distribution.

5. Result and Discussion

In the WSN, the experimentation outcomes were attained using the developed approach to implementing the multipath routing as described in this section. The experimentation of the developed multipath routing approach was performed by deviating the conditions and it was estimated on the basis of diverse metrics like delay, throughput, energy, and a number of alive nodes.

Table 1: *Performance analysis of the proposed model*

Comparative analysis	Metrics			
	Delay	Energy	Throughput	Number of alive nodes
PSO	0.2686	0.0011	0.1666	4
FABC	0.2888	0.0646	0.1666	4
GA	0.4688	0.0027	0.1666	26
ACO	0.2782	0.0268	0.1666	11
BOA	0.4606	0.0408	0.1666	12
Proposed algorithm	0.2626	0.0764	0.6	29

The performance analysis of the developed technique with the conventional approaches is shown in Table 1. The outcomes of the comparative approaches are summarized on the basis of the parameters, such as alive nodes, delay, energy, and throughput. Here, the optimal performance of the comparative approaches is shown when the network is considered with 100 nodes. The adopted method establishes appropriate multipath for the WSN routing and has attained better performance for the delay, energy, throughput, and a number of alive nodes, correspondingly.

6. Conclusion

In WSN, to improve communication a new multipath routing technique was proposed in this paper. Here, the complete design model possesses 2 important schemes namely multipath routing and CHS. The WSN nodes experience the clustering at the time of CHS on the basis of the Taylor kernel FCM method. By exploiting the important constraint such as trust, energy and distance, the CHS was performed. For this, a new optimization approach named the C-SSO algorithm is adopted to identify the optimal multipath. Moreover, on the basis of the constraints namely energy, QoS, and trust the fitness factor was developed. By this, the proposed model has the ability to discover the appropriate multipath for the routing and performs the communication in WSN. At last, the adopted model was experimented within two diverse WSN environments with numerous nodes and hop count. The outcomes of the proposed method were evaluated with the conventional methods on the basis of the constraints such as energy, delay, number of alive nodes, and throughput. From the outcomes, it was clearly evident that the adopted model-based multipath routing model attained enhanced results in terms of delay, throughput, energy, and the number of alive nodes, correspondingly.

Compliance with Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.

Human participants: The conducted research follows the ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

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