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Research Article

Taylor-Spotted Cat Optimization (Taylor-SCO): An Energy-Efficient Cluster Head Selection Algorithm with Improved Trust Factor for Data Routing in WSN

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Wireless Sensor Network (WSN) has inexpensive, small, and less energy sensor nodes, which are allocated in random ways in particular areas for measuring the phenomenon or events in that field. In recent days, WSN has played a vital role in various applications, like industrial monitoring, medical treatments, agricultural monitoring, and military operations. However, the security challenges and network lifetime are the main issues in the existing methods. In order to overcome these issues, the Taylor-Spotted Cat Optimization (Taylor-SCO) approach is devised in this paper. Here, the Cluster Heads (CHs) are selected based on the developed optimization method, named Taylor CSO. Moreover, the delay, distance, and energy parameters are considered for effective Cluster Head Selection (CHS). Here, route maintenance is also done for increasing network lifetime and reducing complexities. In addition, the Modified K-Vertex Disjoint Paths Routing (KVDPR) model is established for routing. The modification of KVDPR is carried out using several factors, such as link reliability, throughput, and various trust factors. Moreover, the developed Taylor-SCO algorithm is developed by combining the Spotted Hyena Optimizer (SHO), Cat Swarm Optimization (CSO) algorithm, and Taylor series. The Taylor-SCO achieved better performance with energy consumption, trust, and throughput of 0.00037 J, 0.51, and 793160 kbps.

1. Introduction

WSN is a rising low cost and flexible solution, which permits controlled monitoring of the environment. Generally, WSN includes a huge amount of sensing devices, which can communicate wirelessly and process the data. The sensor nodes are arranged in several environments for executing applications like industrial automation, military surveillance, habitat monitoring, smart grids, and industrial and home automation [1–3]. A large amount of WSN applications determine physical parameters, namely, object position, humidity, and temperature. The energy needed for the transmission of data is hundred times larger than the energy needed for the processing of data [3, 4]. Generally, WSN is a group of sensor nodes, which uses radio waves for communication [5–8]. In addition, WSN is a predictable wireless ad-hoc network where it can gather, combine, and broadcast the data separately [9]. However, the vital problem in WSN is how to accumulate energy of node, when maintaining essential network behavior. Many sensor network platforms are battery operated, and it is significant in excessive energy restriction [3, 10].

Since sensor nodes are activated based on battery, energy efficiency is a main concern in WSN. As a result, energy use is monitored to increase the system's lifespan. The sensor node in a wireless sensor network (WSN) typically has two tasks: gathering data from the physical environment is the first task, and routing data from the sink node and gathering data from the WSN to be processed is the last task. Meanwhile, multihop routing is a familiar method utilized in large-scale networks to transfer data straight to sink nodes [11, 12]. When the communication process is started, WSN faces energy as the main challenge. Therefore, the amount of transmission must be decreased to offer effective routing and achieve an enlarged system lifetime. WSN includes nodes, where coordinated and sensed data is associated. The continual monitoring is a basic example of the WSN system. Additionally, WSN applications experience energy limitations because nodes transmit the acquired data to sink nodes. Therefore, the utilization of various paths to collect data in WSN has the capability of balancing network lifetime and energy [12]. Moreover, the lifetime of the network is embedded in sensor grouping for saving energy and decreasing long-distance communication. Thus, long-distance communication is avoided for enhancing node lifespan [13, 14]. Furthermore, the clustering approach uses a probability value for creating a CH, and it is proficient to communicate with other nodes in a short range. Hence, multihop routing helps for routing process in a network, and it is restricted by energy factor [15, 16]. Here, the delay is decreased, whereas the consumption of energy is high, thus the routing process accumulates the energy [16, 17].

The Fuzzy A-star-based Cost Effective Routing (FACER) is developed for the WSN process in [10, 18]. This approach is employed for identifying the perfect short path from the source node to the sink node. Recently, the optimization methods are developed to select the optimal route to manage secure communication in WSNs [19–21]. Routing is permitted in a professed manner by sensor nodes, and the fuzzy theory is used for finding CHs. Here, the A-star search process is applied for identifying the shortest path. Moreover, the Energy-Aware Cluster-Based Multihop (EACBM) routing model is devised in [10, 22] for WSN. This approach uses clustering knowledge and multihop communication to decrease energy usage. The Application Threshold-based Centralized Energy Efficient Clustering (ATCEEC) approach is introduced in [9, 23]. In [9, 24], Node Density-based Clustering and Mobile Collection (NDCMC) is integrated with hierarchical routing with data collection in WSN. Besides, energy efficiency is enhanced by the distributed clustering technique in [9, 25]. The hybrid distant-dependent clustering approach was developed, and it includes relative distance to Base Station (BS) and residual energy at CHs [9]. Additionally, a protocol, termed as energy-efficient cluster-based routing system using multihop routing and fuzzy logic was developed in [12, 26], where cluster size is dynamic. Here, the fuzzy logic technique and configuration of cluster size are used to implement the protocol. The method, named Two-Tier Distributed Fuzzy Logic-based Protocol (TTDFP), is introduced in [12, 27] to enlarge the WSN lifespan by estimating routing efficiency. In addition, this model is termed as a distribution adaptive system which effectively operates in sensor network applications. This approach utilized fuzzy clustering to optimize WSN performance.

1.1. Motivation. WSN is a quickly developing information acquirement technology which combines the recent attainment of technology with communications, networks, and microelectronics. Therefore, WSN is a necessary element in several domains, such as urban transport systems, industry control, monitoring of the environment, and military. The challenges experienced by the existing CHS approach are described as follows:

(i) The energy conservation, reliability, and security are the major issues in the large-scale WSNs.
(ii) Some methods may have the communication overhead issues.
(iii) The network connectivity maintenance is a challenging issue.

The challenges faced by existing CHS and data routing approaches are considered as the inspiration for devising a novel CHS model. The primary goal of this study is to create the suggested Taylor-SCO algorithm for a successful CHS.

The main contributions of the research are elaborated below:

(i) An efficient CHS selection approach is devised using the Taylor-SCO.
(ii) Here, the developed Taylor-SCO approach is utilized for selecting the best CH to perform secure data routing.
(iii) The developed Taylor-SCO algorithm is a combination of SHO, CSO, and Taylor series.
(iv) In addition, the modified KVDPR model is devised for the routing process.
(v) Furthermore, the fitness function is computed based on energy, distance, delay, link reliability, and throughput.

The remainder of the paper is structured as follows: The literature review and issues with current CHS and data routing methods in WSN are explained in Section 2. The LLT model, mobility model, and system model are all shown in Section 3. The created Taylor-SCO technique for CHS is explained in Section 4, and the Taylor-SCO model's output is shown in Section 5. In Section 6, the paper's conclusion is discussed.

2. Literature Survey

Daneshvar et al. [3] developed a Grey Wolf Optimizer (GWO) for clustering. In this method, solutions were rated based on the current energy of individual sensor nodes and predicted energy. In addition, it uses a clustering scheme in various successive rounds for improving energy efficiency. This approach guarantees balanced and least consumption of energy, but still, it failed to consider fault tolerance schemes for better performance. Vinitha et al. [16] devised a Cat Salp Swarm Algorithm (C-SSA) approach to choose optimal hops in routing. The CHS was carried out based on the Low-Energy Adaptive Clustering Hierarchy (LEACH) protocol. Furthermore, the best path was chosen by a hybrid optimization model with energy parameters, such as delay, intercluster distance, distance, energy, Link Life Time (LLT), and intracluster distance. This model obtained a better tradeoff between the exploration stage and exploitation stage, although this scheme has a high computation time. Pattnaik and Sahu [10] modeled Elephant Herding Optimization (EHO)-Greedy model for routing in WSN. This approach was considered split BS of fixed and mutable for reducing the power consumption. This approach highly decreased energy usage and enhanced the network life span. However, it has not decreased the CH burden. Vijayalakshmi and Anandan [9] presented Tabu Particle Swarm Optimization (PSO) for CHS in WSN. In this model, the LEACH protocol was employed for expanding the network lifetime. Besides, the PSO model was established for estimating the optimal path to transfer data. This model highly increased the network lifetime and energy efficiency, even though, the Tabu-PSO technique failed to eradicate the blockage in a network.

Mehta and Saxena [28] developed a Multiobjective CH-based Energy-aware Optimized Routing (MCH-EOR) algorithm in WSN. Here, the CHS was done with respect to multiple objectives based fitness function. Once CHS was completed, Sail Fish Optimizer (SFO) was devised for choosing the optimal path for transmission of data. This model improved the lifetime of the network but failed in the reduction of the execution time. Vinitha et al. [12] introduced the Taylor-based Cat Salp Swarm Algorithm (Taylor C-SSA) for secure multihop routing in WSN. At first, energy-efficient CHS was done by the LEACH for effectual transmission of data. Furthermore, sensor nodes transmit data to the sink node by selecting the optimal hop. Here, the optimal hop selection was carried out using Taylor C-SSA. Finally, security-aware multihop routing was done by trust models which involved data forwarding rate, indirect trust, direct trust, and integrity trust. This model obtained better performance in terms of delay, throughput and energy, but the computational time was high. Rodrigues and John [29] devised a novel trust-based routing approach for secure routing. In addition, the Chicken Dragonfly (CHicDra) optimization approach was developed for predicting optimal CH in a network. After CHS, multiobjective Taylor Crow optimization model was developed in which trusted nodes were finalized based on trust parameters. At last, an optimally selected path was utilized for secure and energy-efficient data transmission. This approach obtained less delay during data transmission, even though it failed to introduce fuzzy logic for better performance. Sreedharan and Pete [6] presented the Fuzzy Multicriteria Decision Making (MCDM) technique for the routing process. Here, the optimal CH was selected based on a Generalized Intuitionistic Fuzzy Soft Set (GIFSS) which includes shark smell optimization and a genetic algorithm for routing. In this model, nodes were permitted to be set in a cluster structure, and the optimal CH was selected between the numbers of nodes. This routing process obtained better accuracy, although the overhead of computation was high.

3. System Model

Assume a WSN system with e amount of nodes as $K = \{K_1, K_2, \cdots K_s, \cdots K_e\}$, and a single sink node or BS is denoted as D and the entire CHs are represented as $C = \left\{C_1, C_2, \cdots C_t, \cdots C_f\right\}$. The wireless connection among sensor nodes indicates direct communication in a transmission range. Every node has its own communication range and sensor nodes are evenly isolated with length of N_g and O_g meters. Meanwhile, every node includes unique ID, and the nodes are grouped to create a cluster in the network. The BS is located in a network at length of $\left\{0.5\, N_g, 0.5\, O_g\right\}$. The sink node is employed for receiving data packets from other sensor nodes by CH. Moreover, every coordinate rate of N_t and O_t specifies the position of individual sensor nodes. All nodes transmit data packets to a sink node. The CH of individual cluster group is represented as C, which includes the amount of sensor nodes. After the creation of cluster group, nodes transmit a data packet to I with their relevant CH. The WSN system architecture is depicted in Figure 1.

3.1. Energy Model. Here, the initial energy of all nodes is specified as Q_0. Let us assume that the energy of nodes is not rechargeable [30]. The energy dissipated, while transmitting k data bytes is indicated by

$$\begin{aligned} Q_{\text{disi}}\left(K_s\right) &= Q_{\text{elec}} * k + Q_{\text{amp}} * k * \left\|K_s - C_t\right\|^4; \text{ if } \left\|K_s - C_t\right\|^4 \geq z_0, \\ Q_{\text{disi}}\left(K_s\right) &= Q_{\text{elec}} * k + Q_{uz} * k * \left\|K_s - C_t\right\|^2; \text{ if } \left\|K_s - C_t\right\|^2 < z_0. \end{aligned} \tag{1}$$

where Q_{elec} denotes the electronic energy, which considers several factors, such as digital coding, filtering, amplification, modulation, and spreading.

$$Q_{\text{elec}} = Q_{\text{trans}} + Q_{\text{agg}}, \tag{2}$$

where Q_{amp} is the energy of power amplifier, Q_{trans} specifies transmitter energy, Q_{agg} indicates data aggregation energy, and $\left\|K_s - C_t\right\|$ represents the distance between s^{th} node and t^{th} CH. When receiving k bytes of data, the energy dissipated at the receiver end is illustrated by

$$Q_{\text{disi}}\left(C_k\right) = B_{\text{elec}} * k. \tag{3}$$

After receiving or transmitting k data bytes, the energy value of an individual node is updated.

$$\begin{aligned} Q_{l+1}\left(K_s\right) &= Q_l\left(K_s\right) - Q_{\text{disi}}\left(K_s\right), \\ Q_{l+1}\left(C_t\right) &= Q_l\left(C_t\right) - Q_{\text{disi}}\left(C_t\right). \end{aligned} \tag{4}$$

3.2. Mobility Model. The mobility model [31] is employed to identify sensor node movement, and it is utilized to describe velocity changes, acceleration, and position with respect to

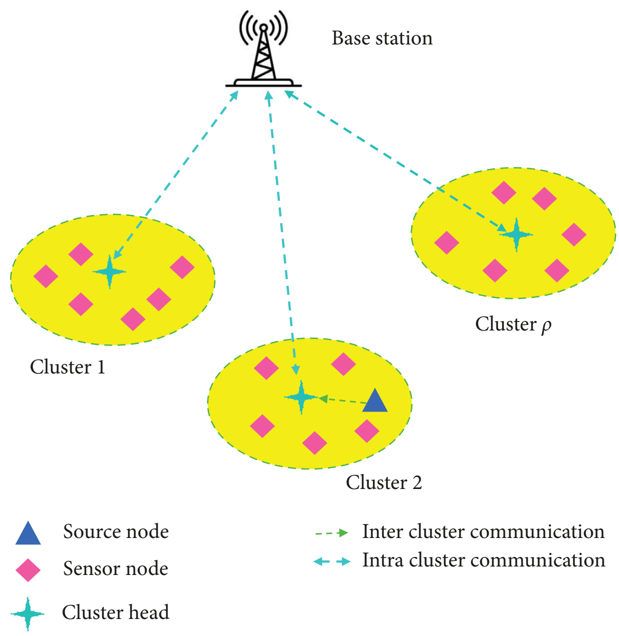


FIGURE 1: System model of WSN network.

time. Let us assume the initial node location s and m as (R_1, S_1) and (R_2, S_2). The nodes s and m moves with various velocities in particular directions with ϕ_1 and ϕ_2 angles. In addition, Euclidean distance between s and m node is represented as

$$W_{(sm,0)} = \sqrt{|R_1 - R_2|^2 + |S_1 - S_2|^2}, \quad (5)$$

where W indicates Euclidean distance between two nodes.

3.3. LLT Model. LLT [32] is computed at every hop during route request packet transmission. All sensor nodes estimated path lifetime between the previous hop and the current hop. The node coordinate s is denoted as (N_s, O_s) and m coordinate node is represented as (N_m, O_m). Along with this, the motion distance of sensor nodes s and m nodes are signified as p_s and p_m, and the mobility speed of s and m nodes is represented as ϕ_s and ϕ_m. The LLT is computed based on the following equation:

$$LLT = \frac{-(ab + xy) + \sqrt{(a^2 + b^2)n^2 - (ay - bx)^2}}{(a^2 + x^2)}, \quad (6)$$

where $a = p_s \cos\phi_s - p_m \cos\phi_m$

$$\begin{aligned} b &= N_s - N_m, \\ x &= p_s \sin\phi_s - p_m \sin\phi_m, \\ y &= N_s - O_m. \end{aligned} \quad (7)$$

4. Proposed Taylor-Spotted Cat Optimization Algorithm for Cluster Head Selection in WSN

The developed Taylor-SCO algorithm for CHS in WSN is described in this section. Here, the nodes are simulated in the WSN network where the nodes are grouped to generate clusters. Once the clusters are generated, then CH is selected by the developed Taylor-SCO approach. Furthermore, the CHS is performed by considering several parameters. Then, the routing process is carried out using modified KVDPR [33]. On the other hand, the modification of KVDPR is made by including various factors, namely trust factors, throughput, and link reliability with distance and energy for effective data routing. Finally, route maintenance is executed for eradicating the obstacles and network failure. Moreover, the developed Taylor-SCO technique is introduced by integrating the CSO algorithm [34], SHO [35], and Taylor series [36]. The block diagram of the Taylor-SCO is depicted in Figure 2.

4.1. Cluster Head Selection Using Proposed Taylor-Spotted Cat Optimization Algorithm. In this section, the CHS process using the developed Taylor CSO is explained. The CHS process is necessary for effective data routing in WSN. In addition, the packet loss is highly decreased and efficient routing is guaranteed by CHS in WSN. In this method, the WSN nodes are initially considered for the CHS process. Here, the CHS is performed using the developed Taylor CSO approach, which is devised by combining SHO [35], CSO algorithm [34] and Taylor series [36]. The CSO algorithm is devised based on the stimulation of behavior of cats. The CSO algorithm mainly includes two modes, such as seeking mode and tracing mode, which inspire the hunting and resting character of the cat. The cat chases prey at replication of the tracing style. Normally, the cat decides the direction and activity speed at seeking mode using the location and speed of prey. On the other hand, SHO is a bio-inspired optimization approach, which imitates the spotted hyena's character. It efficiently utilized to move a search agent towards the global solution by eradicating local optima. Meanwhile, the Taylor series includes the complex variable function, which is the infinite term function expansion. The SHO algorithm and Taylor series are included with CSO for creating optimal solutions for an optimization problem.

4.1.1. Solution Encoding. The solution vector, which identifies CHS to create efficient data routing, is represented by the solution encoding. Nevertheless, a CH is a node that dissipates less energy and has the least amount of delay and distance. Figure 3 shows the solution encoding of the Taylor-SCO. Here, m represents the number of nodes and n specifies the number of CHs.

4.1.2. Fitness Function. The fitness function is calculated considering a number of factors, including distance, latency, and energy dissipation. Additionally, a node with a lower fitness function is chosen to be the CH.

$$\text{Fitness} = \frac{1}{3} \sum_{w=1}^{m} [L_w + M_w + N_w], \quad (8)$$

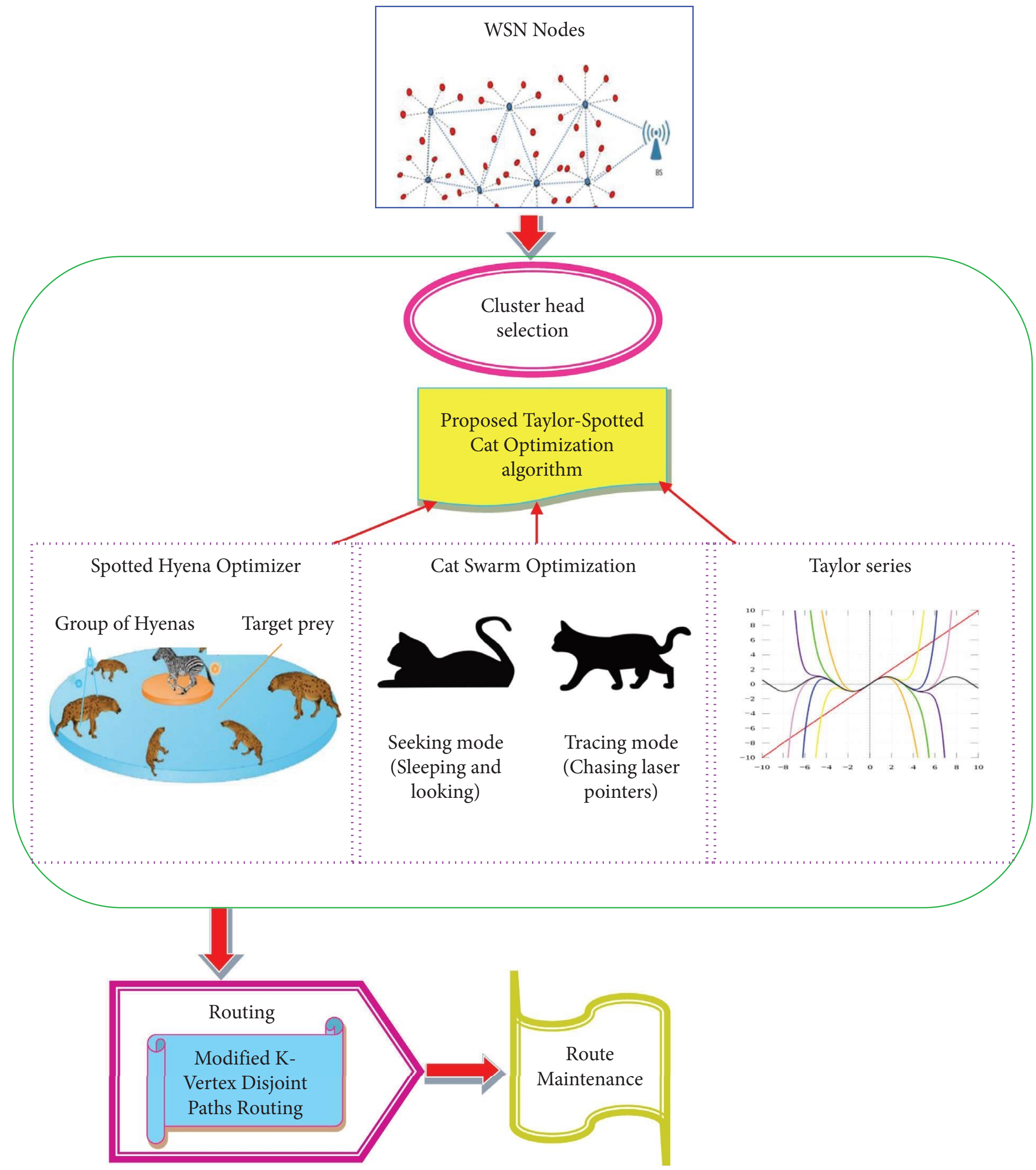


FIGURE 2: Block diagram of developed Taylor-SCO for CHS in WSN.

1	2	⋯	n
1	2	⋯	m

FIGURE 3: Solution encoding of developed Taylor-SCO algorithm.

where L_w indicates node energy, M_w specifies node distance, and N_w represents delay. Here, the delay is estimated by considering the amount of nodes in every cluster group to the whole quantity of nodes in a network.

4.1.3. Algorithmic Process of Developed Taylor-SCO. The algorithmic steps of developing Taylor-SCO for CHS are described below.

(1) Initialization. Initially, the population is initialized as G_r with q overall solutions, which is given by

$$G_r\,(r = 1, 2, \ldots, q), \tag{9}$$

(2) Compute Fitness Measure. The fitness measure of every search agent is used for selecting the CH, and the fitness value computation is indicated in equation (8).

(3) Hunting Process. Spotted hyenas are able to locate the prey and typically survive in packs in this area. While residual search agents form a group towards the optimal solution, the optimal search agent possesses knowledge regarding the prey's position. To update the location, the best solutions are also kept. The spotted hyena's propensity for hunting is demonstrated by

$$\begin{aligned}\vec{A}_d &= |\vec{H}\cdot\vec{G}_r - \vec{G}_K|,\\ \vec{G}_K &= \vec{G}_r - \vec{B}\cdot\vec{A}_d,\\ \vec{M}_d &= \vec{G}_K + \vec{G}_{K+1} +,\ldots,+ \vec{G}_{K+x},\end{aligned} \tag{10}$$

where the representation of the best-spotted hyena location is $\vec{G}_r$, the other spotted hyenas location representation is $\vec{G}_k$, X specifies the whole amount of spotted hyenas, and $\vec{H}$ and $\vec{B}$ represent the coefficient vector, and it is illustrated by

$$\begin{aligned}\vec{H} &= 2\cdot I_1\\ \vec{B} &= 2\vec{c}\cdot I_2 - \vec{c}\\ \vec{c} &= 5-\left(l*\left(\frac{5}{l_{\max}}\right)\right);\quad l = 1,2,..l_{\max}\end{aligned} \tag{11}$$

where I_1 and I_2 are a random number ranging from $[0, 1]$ and $\vec{c}$ linearly decreased from 5 to 0.

(4) Encircling Behavior Based Solution Update. The spotted hyena is typically the most adept at locating its victims and surrounding them. Target prey is currently the best option because it is almost at an optimal value. Remaining agents adjust their places once the optimal search agent has been determined. The modified answer for the spotted hyena's encircling character is shown here as

$$\vec{G}(l+1) = \frac{1}{(l-2\vec{\mathrm{B}})}\left\{\vec{G}_x(l)(l-\vec{\mathrm{B}}\vec{\mathrm{H}}) - 2\vec{\mathrm{B}}\begin{bmatrix}1.3591\vec{G}(l-1) - 1.359\vec{G}(l-2) + 0.6795\vec{G}(l-3)\\ -0.2259\vec{G}(l-4) + 0.0555\vec{G}(l-5) - 0.0104\vec{G}(l-6)\\ +1.38e^{-3}\vec{G}(l-7) - 9.92e^{-5}\vec{G}(l-8)\end{bmatrix}\right\}, \tag{12}$$

where $\vec{G}_x(l)$ specifies the location prey vector, and $\vec{B}$ and $\vec{H}$ are coefficient vectors. On the other hand, the tracing mode equation of the CSO algorithm is illustrated as

$$\begin{aligned}\vec{G}(l+1) &= \vec{G}(l) + F(l),\\ \vec{G}(l+1) &= \vec{G}(l) + F(l) + i_1 j_1\left(\vec{G}_{\text{best}} - \vec{G}(l)\right),\\ \vec{G}(l+1) &= \vec{G}(l) + F(l) + i_1 j_1\vec{G}_{\text{best}} - i_1 j_1\vec{G}(l),\\ \vec{G}(l+1) &= \vec{G}(l)(1-i_1 j_1) + F(l) + i_1 j_1\vec{G}_{\text{best}},\\ \vec{G}_{\text{best}} &= \frac{\vec{G}(l+1) - \vec{G}(l)(1-i_1 j_1) - F(l)}{i_1 j_1}.\end{aligned} \tag{13}$$

Since $\vec{G}_X(l)$ is a target position, $\vec{G}_{\text{best}} = \vec{G}_X(l)$.

To find the best answer, the tracing mode equation of the CSO method is also merged with Taylor-SHO. Equation (12) is substituted for equation (13)

$$\vec{G}(l+1) = \frac{1}{(1-2\vec{\mathrm{B}})}\left\{\frac{\vec{G}(l+1) - \vec{G}(l)(1-i_1 j_1) - F(l)}{i_1 j_1}(1-\vec{\mathrm{B}}\vec{\mathrm{H}}) - 2\vec{\mathrm{B}}\begin{bmatrix}1.3591\vec{G}(l-1) - 1.359\vec{G}(l-2)\\ +0.6795\vec{G}(l-3) - 0.2259\vec{G}(l-4)\\ +0.0555\vec{G}(l-5) - 0.0104\vec{G}(l-6)\\ +1.38e^{-3}\vec{G}(l-7) - 9.92e^{-5}\vec{G}(l-8)\end{bmatrix}\right\}, \tag{14}$$

$$\vec{G}(l+1)=\frac{1}{(l-2\vec{\mathrm{B}})}\frac{\vec{G}(l+1)}{i_1 j_1}(1-\vec{\mathbf{B}}\vec{\mathrm{H}})-\frac{1}{(1-2\vec{\mathrm{B}})}\begin{cases}\dfrac{\vec{G}(l)(1-i_1 j_1)+F(l)}{i_1 j_1}(l-\vec{B}\vec{H})+2\vec{B},\\ 1.3591\vec{G}(l-1)-1.359\vec{G}(l-2),\\ +0.6795\vec{G}(l-3)-0.2259\vec{G}(l-4),\\ +0.0555\vec{G}(l-5)-0.0104\vec{G}(l-6),\\ +1.38e^{-3}\vec{G}(l-7)-9.92e^{-5}\vec{G}(l-8).\end{cases} \tag{15}$$

$$\vec{G}(l+1)-\frac{1}{(l-2\vec{\mathrm{B}})}\frac{\vec{G}(l+1)}{i_1 j_1}(l-\vec{\mathrm{B}}\vec{\mathrm{H}})=-\frac{1}{(l-2\vec{\mathrm{B}})}\left\{\begin{array}{c}\dfrac{\vec{G}(l)(l-i_1 j_1)+F(l)}{i_1 j_1}(l-\vec{B}\vec{H})+2\vec{B},\\ \left[\begin{array}{c}1.3591\vec{G}(l-1)-1.359\vec{G}(l-2),\\ +0.6795\vec{G}(l-3)-0.2259\vec{G}(l-4),\\ +0.0555\vec{G}(l-5)-0.0104\vec{G}(l-6),\\ +1.38e^{-3}\vec{G}(l-7)-9.92e^{-5}\vec{G}(l-8),\end{array}\right]\end{array}\right\}, \tag{16}$$

$$\vec{G}(l+1)\left[1-\frac{1}{(l-2\vec{\mathrm{B}})}\right]\frac{1-\vec{\mathrm{B}}\vec{\mathrm{H}}}{i_1 j_1}=-\frac{1}{(1-2\vec{\mathrm{B}})}\begin{cases}\dfrac{\vec{G}(l)\left(1-i_1 j_1\right)+F(l)}{i_1 j_1}(l-\vec{B}\vec{H})+2\vec{B},\\ 1.3591\vec{G}(l-1)-1.359\vec{G}(l-2),\\ +0.6795\vec{G}(l-3)-0.2259\vec{G}(l-4),\\ +0.0555\vec{G}(l-5)-0.0104\vec{G}(l-6),\\ +1.38e^{-3}\vec{G}(l-7)-9.92e^{-5}\vec{G}(l-8).\end{cases} \tag{17}$$

$$\vec{G}(l+1)\left[\frac{(1-2\vec{\mathrm{B}})(i_1 j_1)-1+\vec{\mathrm{B}}\vec{\mathrm{H}}}{(1-2\vec{\mathrm{B}})(i_1 j_1)}\right]=-\frac{1}{(1-2\vec{\mathrm{B}})}\left\{\begin{array}{c}\dfrac{\vec{G}(l)(1-i_1 j_1)+F(l)}{i_1 j_1}(1-\vec{B}\vec{H})+2\vec{B}\\ \left[\begin{array}{c}1.3591\vec{G}(l-1)-1.359\vec{G}(l-2)\\ +0.6795\vec{G}(l-3)-0.2259\vec{G}(l-4)\\ +0.0555\vec{G}(l-5)-0.0104\vec{G}(l-6)\\ +1.38e^{-3}\vec{G}(l-7)-9.92e^{-5}\vec{G}(l-8)\end{array}\right]\end{array}\right\}, \tag{18}$$

$$\vec{G}(l+1)=\left[\frac{i_1 j_1(1-2\vec{B})}{i_1 j_1(1-2\vec{B})-1+\vec{B}\vec{H}}\right]\left\{\frac{1}{(1-2\vec{B})}\left[\begin{array}{c}\dfrac{\vec{G}(l)(1-i_1 j_1)+F(l)}{i_1 j_1}(1-\vec{B}\vec{H})+2\vec{B}\\ \left[\begin{array}{c}1.3591\vec{G}(l-1)-1.359\vec{G}(l-2)+0.6795\vec{G}(l-3)\\ -0.2259\vec{G}(l-4)+0.0555\vec{G}(l-5)-0.0104\vec{G}(l-6)\\ +1.38e^{-3}\vec{G}(l-7)-9.92e^{-5}\vec{G}(l-8)\end{array}\right]\end{array}\right]\right\}, \tag{19}$$

where i_1 ranges from $[0,1]$ and j_1 is constant $F(l)$ signifies the velocity of the cat.

(5) Feasibility Checking. The least fitness measure is considered as best result.

(6) Termination. The aforementioned steps are repetitive until the best solution is achieved. The pseudocode of the Taylor-SCO is illustrated in Algorithm 1.

4.2. Secured KVDPR Technique for Data Routing. Once the CHs are selected, data routing is achieved based on the modified KVDPR method. The modified KVDPR scheme is developed by modifying the KVDPR model, and it utilizes various parameters, like average distance, residual energy, link reliability, and trust of the CHs. Normally, modified KVDPR [33] determined k-disjoint paths between the sink node and CH. Moreover, modified KVDPR is a distributed technique in which individual CH chooses a k-vertex disjoint path using average distance, link reliability, residual energy, and trust.

Here, the residual energy is estimated based on the following equation:

$$R_{\text{ene}}=\frac{\sum_{o=1}^{V} A_{cur(o)}(I)}{V}, \tag{20}$$

where I specifies the vertices amount, A_{cur} is an energy value at the current level, and I denotes the node.

Moreover, the CH estimates the average distance based on the below equation:

$$B_d=\frac{\sum_{o=1}^{V} B_d(I)}{V}. \tag{21}$$

The link reliability is estimated by

$$\chi=\text{probability}\,(Y)=e^{-\beta Y}, \tag{22}$$

where Y specifies average link failure, which is the inverse of link lifetime $(Y=1/\mathrm{T})$, and T indicates link lifetime.

In addition, in the trust factor, every node obtains a trust degree value for all of its neighbors. Trust value [37] is a measure of the trust level in its neighbor. Furthermore, the trust value is estimated by local information, like local topology details. The trust of CHs is estimated by

$$L\left(CH_{\mathrm{Y,Z}}\right)=P_1 L_{\mathrm{Y,Z}}^{dt}(i)+P_2 L_{\mathrm{Y,Z}}^{idt}(i), \tag{23}$$

where $L_{\mathrm{Y,Z}}^{\mathrm{dt}}(i)$ is a direct trust, $L_{\mathrm{Y,Z}}^{id}(i)$ represents the indirect trust. P_1 and P_2 are weighting factors in which $P_1+P_2=1$. Moreover, the direct trust is expressed as

$$L_{\mathrm{Y,Z}}^{dt}(i)=\frac{E_{\mathrm{YZ}}(i)}{H_{\mathrm{YZ}}(i)}, \tag{24}$$

where $H_{\mathrm{YZ}}(i)$ signifies the number of packets forwarded from Z^{th} CH CH at time i, and $E_{\mathrm{YZ}}(i)$ is a number of packets successfully received by Z^{th} CH CH from Y^{th} CH CH at time i.

Similarly, the indirect trust is formulated as

$$L_{\mathrm{Y,Z}}^{idt}(i)=\frac{1}{O}\sum_{\mathrm{T}=1}^{\mathrm{O}} L_{\mathrm{EZ}}^{dt}(i), \tag{25}$$

where O is the amount of CH selected for the routing process. Therefore, routing is performed by considering CHs having maximum trust, link reliability, residual energy, and permitted distance.

4.3. Route Maintenance. The route maintenance process is used for monitoring the delivery function of data packets and depicts the link failure error. The route may not be present between the nodes, while node mobility is increased. Evert CH sets a timer X before the transmission of data. The CH transmits route maintenance requests to every CH in a network once, X terminates, and probability $(Y)>\tau$. Here, the term τ indicates the threshold factor. Thus, CH resets and X carried out a re-routing process.

5. Results and Discussion

This section illustrates the results and discussion of the Taylor-SCO in terms of throughput, energy consumption, and trust.

5.1. Experimental Setup. The implementation of the Taylor-SCO is done in MATLAB tool with 4 GB RAM, Intel i3 processor, and Windows 10 OS. The simulation parameter of the Taylor-SCO is elaborated in Table 1.

```
Input: G_r
Output: \vec{G}(l + 1)
Start
Initialize a parameters, c, H, B, and X
Estimate the fitness function
Group every far optimal solution
while (l < l_max) do
    for every search agent do
        Change the location of the search agent using equation (19)
    end for
        Verify whether any search agent moves away from the search space
        Group update
l = l + 1
end while
return the best solution
Stop
```

Algorithm 1: Pseudocode of developed Taylor-SCO technique.

Table 1: Simulation parameter.

Free space energy	10*0.000000000001
Receiver energy	50*0.00000000151
Transmitter energy	50*0.00000000014
Energy of power amplifier	0.00136*0.00000000001
Energy of data aggregation	5*0.000000001

5.2. Performance Metrics

5.2.1. Throughput. Throughput is a measure, which identifies the amount of data packets transmitted through a channel with regards to a particular time interval.

5.2.2. Energy Consumption. It is a measure used to estimate the amount of energy consumed during the execution process.

5.2.3. Trust. Trust is a performance metric estimated to identify the trust level of neighbor, which is expressed in Section 4.2.

5.3. Experimental Result. Figure 4 displays the experimental outcome of the Taylor-SCO with several nodes. Figure 4(a) shows the simulation result of the Taylor-SCO with 50 nodes, Figure 4(b) represents the simulation outcome of the Taylor-SCO with 100 nodes, and the simulation result of the Taylor-SCO with 150 nodes is depicted in Figure 4(c).

5.4. Comparative Methods. The existing approaches, namely, Distributed Energy Efficient Heterogeneous Clustering (DEEHC) [33], GWO [3], Tabu PSO [9], EHO-Greedy [10], Taylor-Spotted Hyena Optimization (Taylor-SHO) algorithm, C-SSA [16], and MCH-EOR [28] are analyzed for evaluating the performance of Taylor-SCO.

5.5. Comparative Analysis. This section deliberates the comparative analysis of the Taylor-SCO with respect to 50, 100, and 150 nodes.

5.5.1. Comparative Analysis Using 50 Nodes. The analysis of the Taylor-SCO for 50 nodes by varying the number of rounds is expressed in Figure 5. The analysis of energy consumption is depicted in Figure 5(a). The energy consumption of existing methods, like GWO, DEEHC, EHO-Greedy, Tabu PSO, C-SSA, MCH-EOR, and Taylor-SHO are 0.00178 J, 0.00201 J, 0.00161 J, 0.0017 J, 0.00203 J, 0.00181 J, and 0.00089 J, and Taylor-SCO achieved 0.00069 J at 100^{th} round. Moreover, the analysis of throughput is shown in Figure 5(b). At 100^{th} round, the throughput value of GWO is 978.43 kbps, DEEHC is 955.94 kbps, EHO-Greedy is 940.60 kbps, Tabu PSO is 920.16 kbps, C-SSA is 946.38456 kbps, MCH-EOR is 968.652432 kbps, Taylor-SHO is 1022.4 kbps, and Taylor-SCO obtained 1124.64 kbps. Likewise, Figure 5(c) represents the analysis of trust by varying number of rounds. The trust value obtained by Taylor-SCO is 0.525, when the GWO is 0.503, DEEHC is 0.502, EHO-Greedy is 0.502, Tabu PSO is 0.506, C-SSA is 0.497, MCH-EOR is 0.498, and Taylor-SHO is 0.517 for 100 numbers of rounds.

5.5.2. Analysis Based on 100 Nodes. Figure 6 depicts the analysis of the Taylor-SCO for 100 nodes by changing the round. Figure 6(a) represents the analysis of energy consumption. The energy consumption value obtained by Taylor-SCO is 0.000362 J, when the GWO is 0.00089 J, DEEHC is 0.00111 J, EHO-Greedy is 0.00071 J, Tabu PSO is 0.00080 J, C-SSA is 0.00113 J, MCH-EOR is 0.00090 J and Taylor-SHO is 0.00044 J for 100 numbers of rounds. Figure 6(b) shows the analysis of throughput. At 100^{th} round, the throughput value of GWO is 1223.04 kbps, DEEHC is 1194.93 kbps, EHO-Greedy is 1175.76 kbps, Tabu PSO is 1150.2 kbps, Taylor-SHO is 1329.12 kbps, C-SSA is 1182.98 kbps, MCH-EOR is 1210.82 kbps, and Taylor-SCO obtained 1462.03 kbps. Additionally, the analysis of trust is illustrated in Figure 6(c). The trust value of GWO, DEEHC, EHO-Greedy, Tabu PSO, C-SSA, MCH-EOR, and Taylor-SHO is 0.504, 0.502, 0.505, 0.502, 0.497, 0.499, and 0.527, and the Taylor-SCO is 0.533 at 100^{th} round.

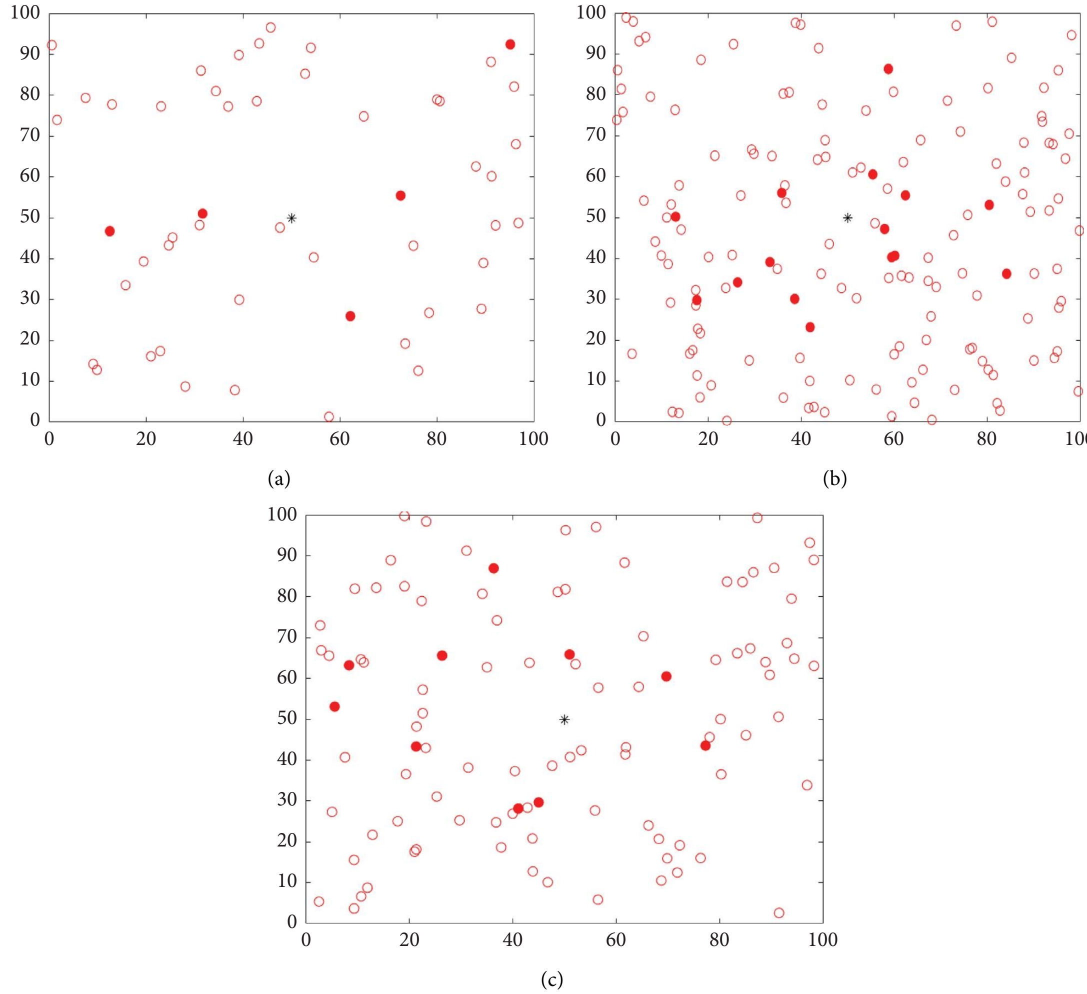
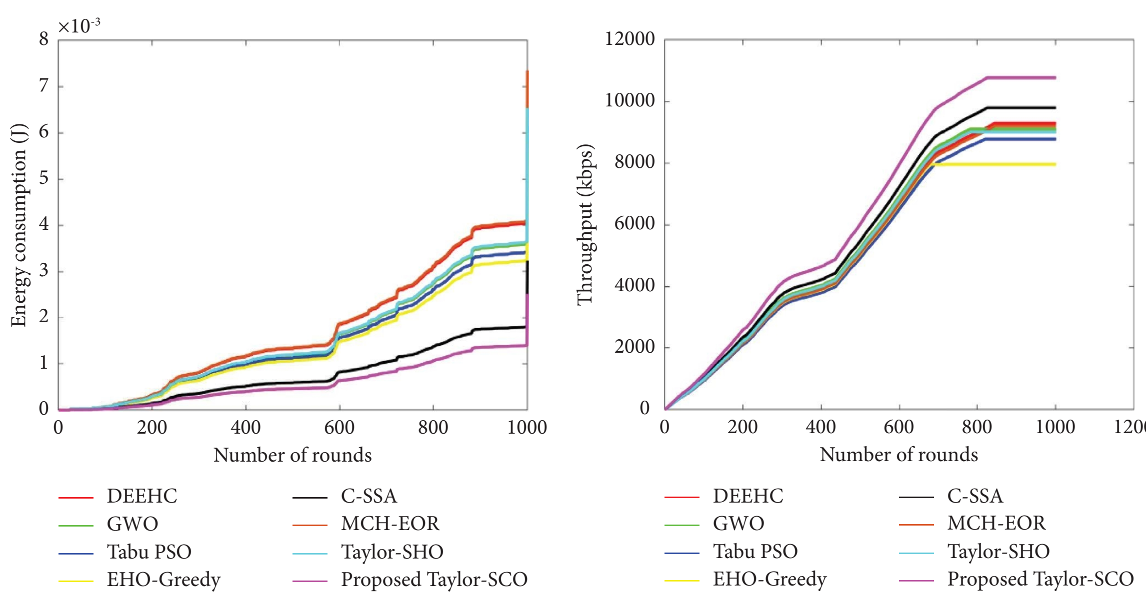
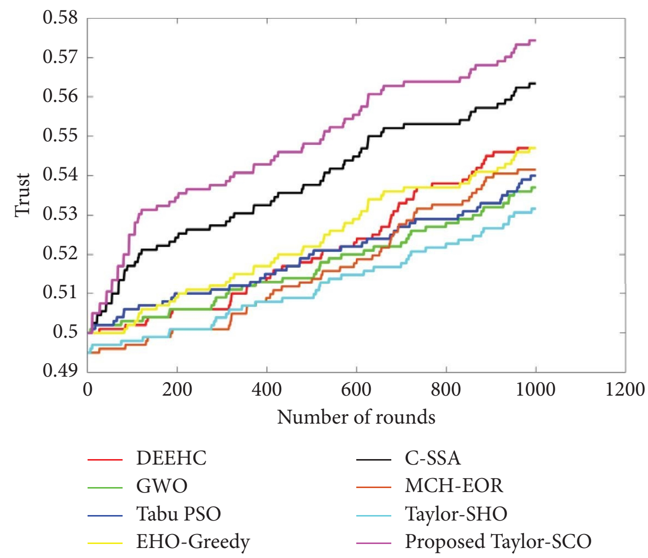


Figure 4: Simulation results of developed Taylor-SCO method for, (a) 50 nodes, (b) 100 nodes, and (c) 150 nodes.



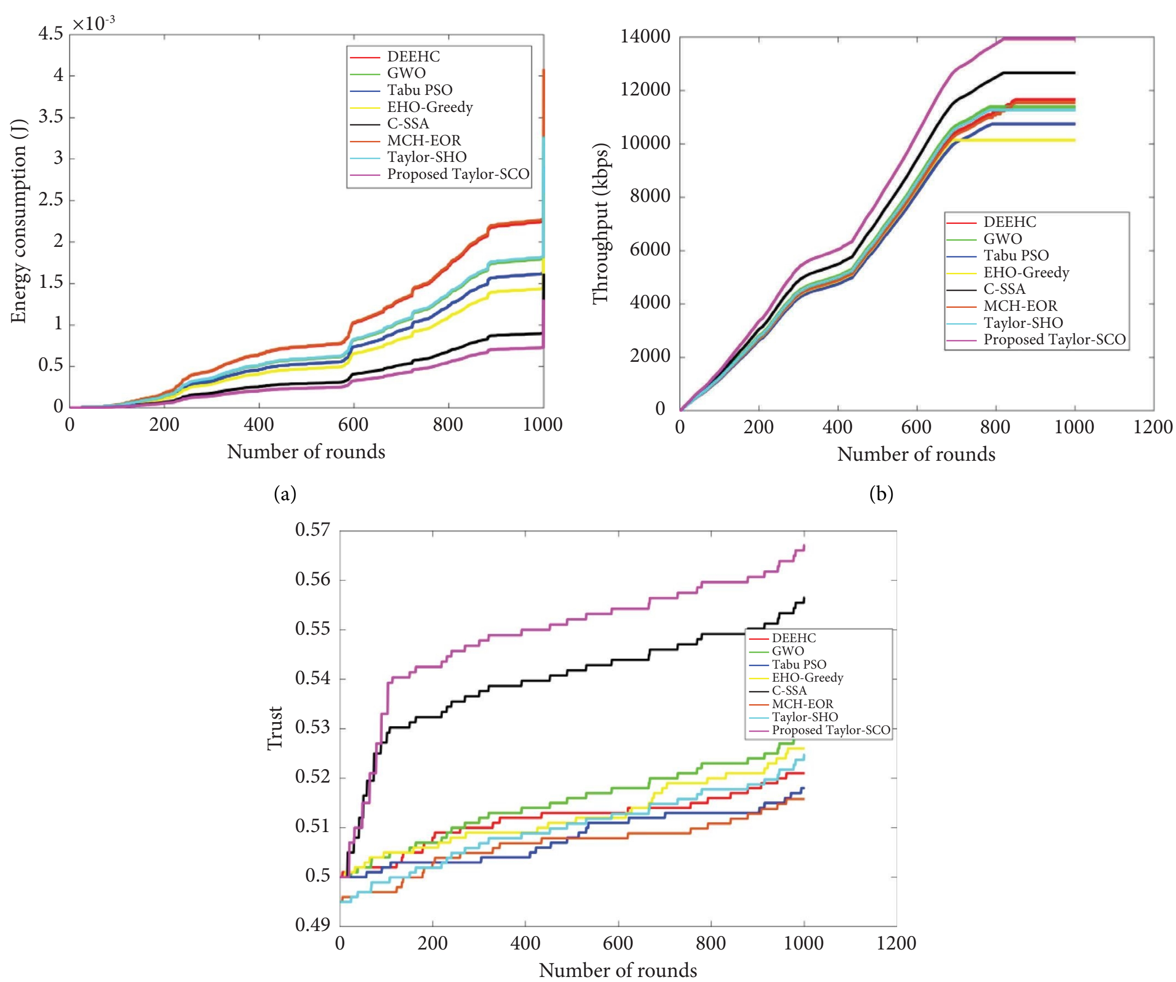
(a) (b)

Figure 5: Continued.



(c)

Figure 5: Comparative analysis of developed Taylor-SCO with 50 nodes, (a) energy consumption, (b) throughput, (c) trust.



(c)

Figure 6: Comparative analysis of Taylor-SCO with 100 nodes, (a) energy consumption, (b) throughput, (c) trust.

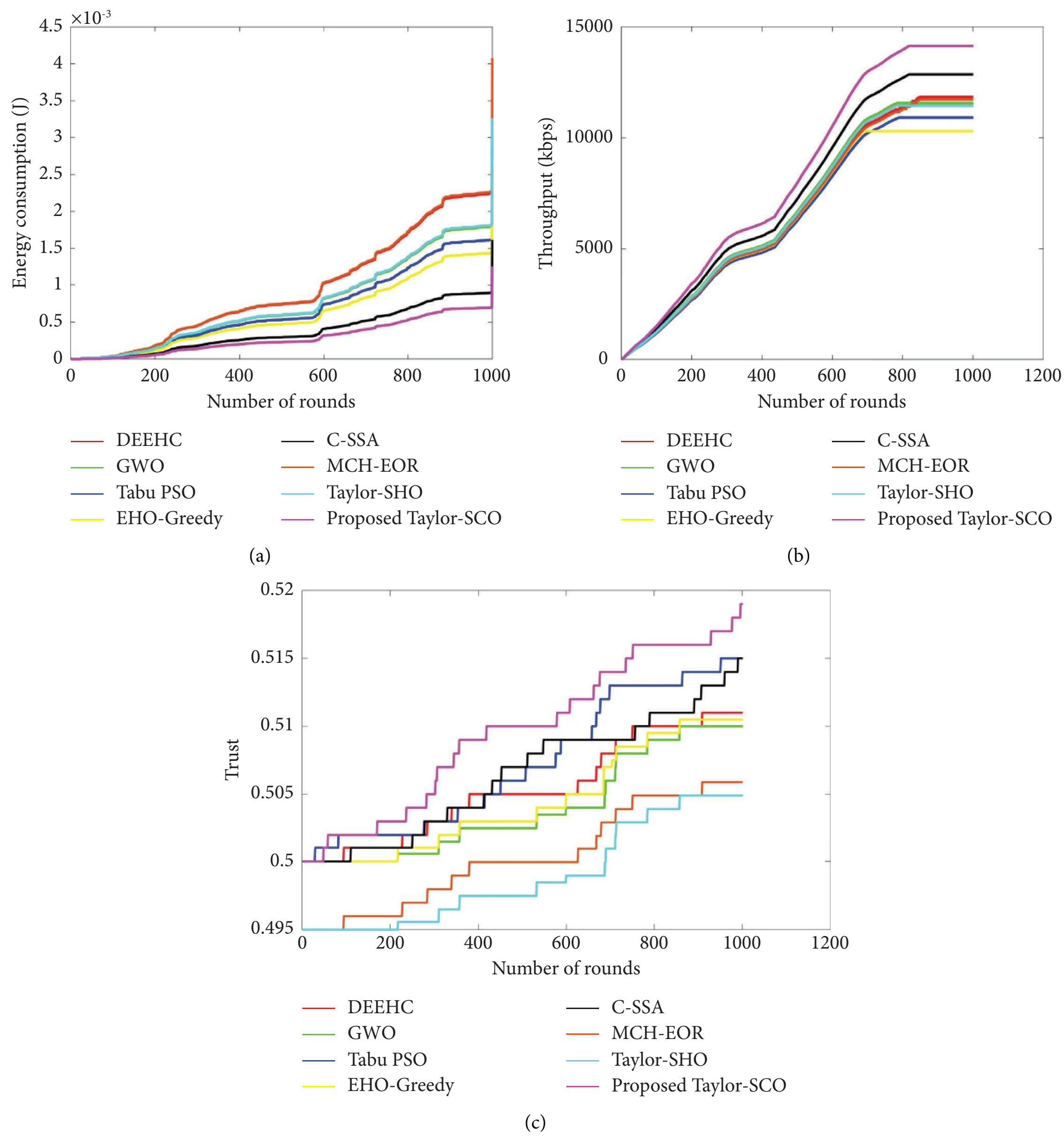


Figure 7: Comparative analysis of Taylor-SCO with 150 nodes, (a) energy consumption, (b) throughput, (c) trust.

5.5.3. Analysis Based on 150 Nodes. The analysis of the developed Taylor-SCO model with respect to energy consumption, throughput, and trust for 150 nodes by varying the number of rounds is expressed in Figure 7. The analysis of energy consumption by varying the rounds is depicted in Figure 7(a). At 100th round, the energy consumption of DEEHC is 0.00111 J, GWO is 0.00089 J, Tabu PSO is 0.00080 J, EHO-Greedy is 0.00071 J, C-SSA is 0.00113 J, MCH-EOR is 0.00090 J, Taylor-SHO is 0.00044 J, and Taylor-SCO obtained 0.00034 J. In addition, the analysis of throughput by varying number of rounds is displayed in Figure 7(b). The throughput of existing methods, like DEEHC, GWO, Tabu PSO, EHO-Greedy, C-SSA, MCH-EOR, and Taylor-SHO are 1212.94 kbps, 1241.48 kbps, 1167.53 kbps, 1193.48 kbps, 1200.81 kbps, 1229.07 kbps, and 1349.15 kbps, and Taylor-SCO algorithm obtained1484.07 kbps at 100th round. Figure 7(c) represents the analysis of trust by varying number of rounds. The trust value obtained by Taylor-SCO is 0.502, when the existing method, such as DEEHC is 0.501, GWO is 0.5, Tabu PSO is 0.502, EHO-Greedy is 0.5, C-SSA is 0.496, MCH-EOR is 0.495, and Taylor-SHO is 0.5 for 100 numbers of rounds.

5.6. Comparative Discussion. The comparative analysis of several existing approaches and Taylor-SCO is deliberated in this section. Table 2 depicts the comparative discussion of the developed method with respect to energy consumption, trust, and throughput. From the below table, it is well noted that the Taylor-SCO obtained less energy consumption of 0.00037 J, a high throughput of 7931.60 kbps, and a high trust of 0.51 with 150 nodes.

Table 2: Comparative discussion.

Metrics/methods	DEEHC	GWO	Tabu PSO	EHO-Greedy	C-SSA	MCH-EOR	Taylor-SHO	Proposed Taylor-SCO
50 nodes								
Energy consumption (J)	0.00217	0.00193	0.00183	0.00174	0.00220	0.00195	0.000967	0.00075
Throughput (kbps)	5109.02	5229.23	4917.78	5027.06	5057.9	5176.9	5464.2	6010.62
Trust	0.518	0.514	0.52	0.522	0.513	0.509	0.537	0.54
100 nodes								
Energy consumption (J)	0.00120	0.000967	0.000870	0.000774	0.00122	0.00098	0.000483	0.00039
Throughput (kbps)	6386.28	6536.54	6147.22	6283.83	6322.42	6471.18	7103.46	7813.80
Trust	0.513	0.516	0.508	0.511	0.508	0.511	0.541	0.55
150 nodes								
Energy consumption (J)	0.00120	0.000966	0.000869	0.00077	0.00136	0.00108	0.000483	0.00037
Throughput (kbps)	6482.55	6635.08	6239.89	6378.55	6417.73	6568.74	7210.54	7931.60
Trust	0.505	0.5025	0.506	0.503	0.500	0.497	0.507	0.51

Table 3: Computational time.

Methods	DEEHC	GWO	Tabu PSO	EHO-Greedy	C-SSA	MCH-EOR	Taylor-SHO	Proposed Taylor-SCO
Computational time (sec)	15.878	14.687	13.782	13.099	12.098	11.099	10.810	9.875

5.7. Computational Time. The computational time of the models are depicted in Table 3. Here, due to the integration of the optimization algorithm, the devised Taylor-SCO needed a minimum computational time of 9.875 sec.

6. Conclusion

This paper presents an efficient CHS technique, named as Taylor CSO technique. At first, the WSN nodes are simulated in a network where the nodes are grouped to create clusters. After that, the CH is selected based on the Taylor-SCO. The developed method selects the CH based on fitness function using the factors, such as energy dissipation, delay, trust, and distance. Once the CHS is completed, a routing approach is carried out using modified KVDPR. The modification of KVDPR is performed by various parameters, like link reliability, energy, distance, throughput, and various trust factors for executing effective data routing. Finally, route maintenance is performed for eradicating the complexities and failure of the network. The performance of the Taylor-SCO is evaluated using energy consumption, trust, and throughput with better performance of 0.00037 J, 0.51, and 793160 kbps. The future work of the research would be the development of other optimization techniques for effective CHS for enhancing the performance of the network during data routing.

Data Availability

The data that supports the findings of this study are available within the article. The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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