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RESEARCH ARTICLE

DBKNN and Radial-ANFIS Model for Energy Efficient Wireless Sensor Network

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ABSTRACT In a Wireless Sensor Network (WSN), packet transmission and sensing functions are the most energy consumption factors. When it comes to wireless communication, unnecessary sensing could increase data communication which in turn needs the biggest amount of energy for communication. Thus, to minimize Energy Consumption (EC), various research has been conducted. Still, they don't provide efficient EC. To solve this issue, a novel Davies-Bouldin K Nearest Neighbor (DBKNN) and Radial-Adaptive Neuro Fuzzy Interference System (Radial-ANFIS) model is proposed for energy-efficient WSNs. Initially, partitioning is performed on deployed nodes. Then, node features are extracted. By employing Laplacian Cubic Cheetah Optimizer (LCCO), CHs are selected using features; then, nodes are clustered using DBKNN. Next, weights are assigned to each clustered node. By employing Adaptive Intensed Golden Tortoise Beetle Optimizer (AI-GTBO), relay nodes are selected using weight value. Paths are created betwixt the node and Base Station (BS) utilizing relay nodes; then, the shortest path is computed. Nodes sense the data once the network is designed, and the correlation between each data is calculated. For redundant node detection, the analytic output is given to Radial-ANFIS. Lastly, redundant nodes are kept to sleep, and the remaining node data are utilized for transmission. When data is transmitted to BS, its first dimension is reduced using Newton Raphson Iterative Principal Component Analysis (NRI-PCA). According to outcomes, the proposed model reduces EC and maximizes the overall throughput and network lifetime compared to other methods. The EC rate is also reduced to 1364 J using the proposed method.

INDEX TERMS AI-GTBO, Davies-Bouldin K Nearest Neighbor, Laplacian Cubic Cheetah Optimizer, NRI-PCA, Radial-ANFIS.

I. INTRODUCTION

Wsn technologies have rapidly developed over the years, which contain many small Sensor Nodes (SNs) [1]. Each SN is assigned to three essential functions, namely recognizing vital information, processing the sensed data, as well as transferring messages with other SNs [2], [3]. More energy is taken by the communication amongst the SNs; therefore, the number of inter-node communications should be reduced for conserving energy [4], [5]. Also, SNs are wielded for random deployment in harsh as well as inaccessible environments, making failed nodes' recharge either impossible or else uneconomical. Hence, it is challenging to build an energy-efficient system, which resulted in designing a design protocol [6]. The two propitious fields for WSNs are energy-efficient clustering together with routing algorithms. The process of determining the best path from the SN to BS for extending the network lifetime by keeping sensors alive is termed clustering-based routing, which is constructed to be energy-efficient for data transferring [7]. In clustering-centric techniques, SNs are grouped into small clusters [8]. Some nodes would be chosen as Cluster Heads (CH), thus aggregating the data sent by the nodes in the cluster. For processing and transmitting data to the BS, nodes with superior energy might be chosen as CH [9]. The key principle in clustering is to localize message transmission within clusters, and between CHs and BS, which has numerous benefits like preserving the bandwidth, averting redundancy, and reducing communication overhead [10]. Several techniques like Low Energy Adaptive Clustering

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Hierarchy (LEACH), Stable Election Protocol (SEP), CO, etc are developed to detect CH in prevailing methodologies. However, these methods are still challenging to provide the best CH. Certain limitations need to be solved for better classification despite developing numerous ML and DL-centered models for the energy-efficient WSN. Accordingly, the proposed model addressed some of the current challenges among the existing methods. Due to delivering the same data from a large number of adjacent nodes, node lifetime is rapidly depleted in the existing approaches. In existing works, a context-aware sensor deployment problem can be solved by an adaptive algorithm, but it is affected by initialization as well as the number of iterations. The appropriate initialization and iteration procedures need to be considered to achieve the objectives within a reasonable computational budget. The traditional Energy-Efficient Routing Protocol (RP) for WSN did not consider the density of the nodes when selecting the CH. CHs are selected randomly in the existing node clustering approaches. It does not select the CHs based on any threshold condition and the sustaining energy at each node after completing each round. These issues will incur energy costs. This stimulates the proposed model to investigate energy-efficient data transmission in a WSN system and proposes a novel DBKNN and Radial-ANFIS classifier. Unlike existing models, the proposed model focuses on a systematic CH selection that enables the SNs to form CH and efficient relay node selection for reducing EC and improving the network's lifetime. The main contributions of the proposed model are outlined as follows,

- Proposed a novel algorithm centered on LCCO for CH selection and optimal energy utilization in WSN. The algorithm converges potential CHs based on residual energy, Node degree, Centrality, Received Signal Strength (RSS), Position of the BS, and the remaining energy of nodes to prevent randomness in CH selection and energy-efficient data deliveries..
- A novel neural network classifier was developed for classifying the state of nodes. This algorithm classifies the node status by the analysis of the correlation between data. Based on the results, the redundant nodes are kept sleep to eliminate unwanted data transmission, and the remaining are allowed for data transmission.
- An efficient relay node selection technique was introduced for selecting relay nodes. This scheme chooses the relay nodes centered on energy, distance, and density of nodes to act as an intermediary for transmitting data, thereby saving EC and improving the network's lifetime.
- An efficient dimension reduction technique is employed for reducing the EC by the transmission of relevant data to the destination. In addition, a well-planned clustering technique that gives proper clustering of the nodes for efficiently sending the data was devised.

The rest of the part is arranged as: the associated work is expounded in section II; the proposed model is elucidated in section III; the proposed technique's results and discussion grounded on performance metrics are elucidated in section IV; the paper is wrapped in section V.

II. LITERATURE REVIEW

In [11] Lilhore et al., developed a depth controlled with an energy-balanced RP. To improve an existing genetic algorithm, encoding, crossover, and mutation improvements were added. The technique's packet delivery ratio and EC was depicted by the outcomes. However, owing to traditional encryption methodology, the hacker might attack the data easily [11]. In [12] Wang et al., explored an Energy Efficient RP centered on an Improved Artificial Bee Colony Algorithm (ABC) for WSN. For resolving the clustering issue in WSNs, an effectual improved ABC algorithm was presented. As per the simulation outcome, when analogized to the prevailing protocols, this technique had a better performance. Nevertheless, this system was not apt to deploy in a dynamic environment. In [13] Reyes et al., recommended a simple energy-aware routing technique entered on the Game of Life cellular automaton. The WSN's discrete dynamic behavior was presented via a set of rules fused with A-star algorithm variation. As per the outcomes, when analogized to recent research works, the system precisely balanced the EC rate whilst expanding the network lifetime. Yet, the workload on the SNs increased drastically.

In [14] Bhushan et al., developed Fuzzy Attribute-centric Joint Integrated scheduling and Tree formation (FAJIT) for tree formation along with parent node selection employing fuzzy logic in a heterogeneous network. Initially, fuzzy logic was implemented. For retrieving normalized weights, min-max normalization was wielded for the graph's edges. Regarding energy efficiency, this system was superior. Nevertheless, for executing the operation, huge power was required. In [15] Alghamdi built a fresh clustering scheme with optimal CH selection by taking '4' major criteria, namely energy, distance, delay, together with security. Moreover, a fresh system, which hybridized the dragonfly concept and firefly algorithm was presented to choose the optimal CHs. This system depicted enhanced performance. However, the data was offered with superior packet loss. In [16] Madhavi et al., explored Energy Efficient Target Tracking in WSN employing Particle Filter-Support Vector Machine (PF-SVM). In several tracking and localization issues, PF was the most accepted filtering technique. This system depicted superior performance in detecting the target location as well as sustaining lower EC. But, by the kind of selection of kernel parameters, the technique's performance was hugely affected. In [17] Khalaf and Abdul sahib presented an energy-efficient routing together with a reliable data transmission protocol in WSN. The overall re-clustering process was reduced in conventional clustering algorithms, thus it had a considerable impact on energy usage. The Energy Efficient Routing (HEESR) algorithm was above its clients in network reliability and scalability. Nevertheless, the memory size was less. In [18] Natarajan explored an enhanced energy-efficient

WSN employing multicast Particle Swarm Optimization (PSO). For augmenting the SN's lifespan, a piezoelectric method with Multicast PSO was suggested. This technique augmented the prevailing methodologies' lifespan. Yet, the detection accuracy was exaggerated by the optimal feature selection devoid of doing the feature extraction phase.

In [19] Muzakkari et al., explored an Energy Efficient and Quality of Service (QoS)-aware (EEQ) Medium Access Control (MAC) protocol with a duty cycle system. The active period length was augmented by nodes when there was high traffic, thus minimizing packet queue waiting times. When analogized to the prevailing energy-aware MAC protocol, the EEQ's effect on augmenting energy efficiency as well as extending WSNs' lifespan might be confirmed. Yet, the time essential to process the data is augmented by the employment of a larger dataset. In [20] Arikumar et al., suggested an Energy Efficient LifeTime Maximization (EELTM). A CH-Cluster Router (CR) selection was wielded for detecting the optimal CR in every cluster. By the chosen CH, the information was collected from the cluster members. The prevailing techniques were surpassed by the EELTM. Nevertheless, the system was easily susceptible to early convergence.

To solve the energy efficiency issue in WSN, in [21] Kathiroli et al., introduced a hybrid sparrow search algorithm with a differential evolution approach. The cluster head selection using the high-level search efficiency of the hybrid algorithm to enhance the network lifetime was the prime intention of the author. The model showed an improvement in residual power and throughput than other algorithms. However, the network performance was poor in addressing large-scale data due to the fixed arithmetic value of parameters. On the other hand, a hybridization of Particle Swarm Optimization (PSO) with Low Energy Adaptive Clustering Hierarchy (LEACH) was developed by Sharmin et al., for WSN [22]. The algorithm's purpose was to aggregate data and save energy by determining CH and adjusting the CH during the clustering process. The results exhibited that the network lifetime was increased, and EC was reduced compared to the other mentioned techniques. The model had increased energy usage due to the existence of coverage and connectivity issues. Similarly, in [23] Rami et al., investigated the improved version of the Grey Wolf Optimization (GWO) algorithm to alleviate the problem of energy efficiency in WSN. The parameters like sink distance, CH balancing factors, residual energy, and average intra-cluster distance were taken into consideration to select optimal CHs. The results confirmed the optimal selection of CHs with minimal EC and enhanced the network lifetime. Nevertheless, the model was ineffective for higher node densities.

III. PROPOSED METHODOLOGY OF ENERGY-EFFICIENT WSN

This paper proposes a novel DBKNN and Radial-ANFIS model for energy-efficient data transmission in WSN. Here, two phases are considered. One is network deployment and the other is data utilization. In the first phase, deployed nodes are clustered and then the shortest path is created. In the second phase, sensed data is transferred to BS. In Figure 1, the proposed technique's block diagram is depicted.

A. NETWORK DEPLOYMENT

This is the initial phase in which the network is built with energy efficiency in mind between the BS and SNs. The steps of network deployment are described further below.

1) NODE INITIALIZATION

Here, the nodes are deployed and initialized. The complexity of WSN problems like routing, data fusion, communication, and so on could be reduced by a proper node deployment. The nodes in the network are static and are left unattended after deployment. Each node only has local information or the identification of its one-hop neighbor nodes. All nodes have similar capabilities, processing, communication, and initial energy. The initialized nodes are written as,

$$\aleph_n = \aleph_1, \aleph_2, \aleph_3, \ldots\ldots \aleph_N \tag{1}$$

Here, $\aleph_n$ implies the *'M'* number of initialized SNs.

2) PARTITION

Here, the nodes are partitioned into four different quadrants, centered on the number of nodes deployed in the monitoring area, to form the monitoring area as a whole. Partioned nodes are denoted as Λ_n.

3) FEATURE EXTRACTION

After partitioning, to gather information about the initialized node, features are extracted for the effective selection of CH. Thus, the necessary sensor features, such as (A) node location, (B) initial energy, (C) node degree, (D) node centrality, (E) the distance betwixt neighboring nodes, (F) the distance between node and BS, (G) received signal strength, and (H) the node ID are extracted. The extracted features are initialized as,

$$F_m = F_1, F_2, F_3, \ldots.F_M \text{ where, } i = 1, 2, 3, \ldots\ldots.M \tag{2}$$

where, $F_m \in \Lambda_n$ implies the number of extracted features.

4) CLUSTER HEAD SELECTION

Here, CHs are selected from F_m using LCCO. By the hunting strategies of cheetahs, the mathematical operation of Cheetah Optimizer (CO) is inspired. However, probing search space's larger portions for determining novel enhanced solutions by a random walk about chosen cheetahs and the best cheetah in the exploration stage is the disadvantage of the existing CO. The random walk is grounded on consistently distributed random numbers. Thus, rather than uniform distribution, Laplace distribution is wielded in CO random walk for surpassing the above issues. For augmenting the population's uniformity and ergodicity, chaos is presented

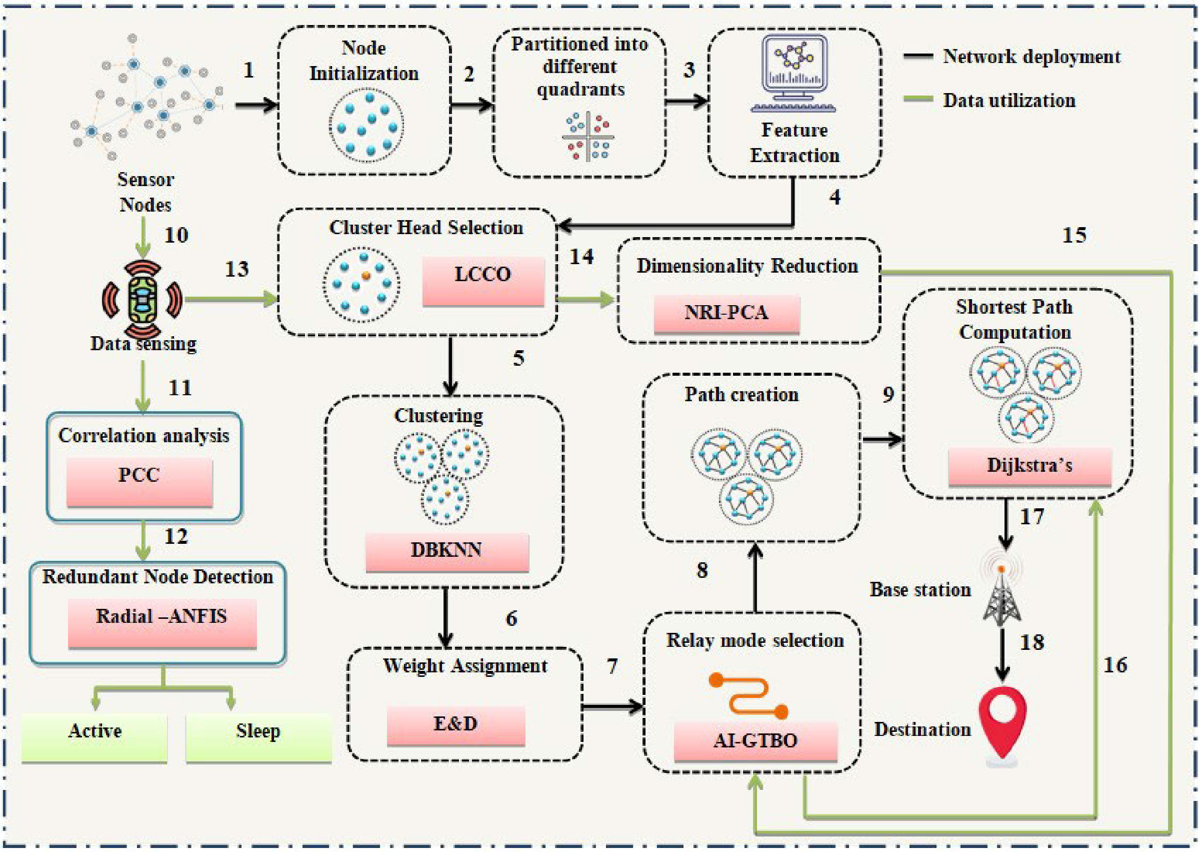

FIGURE 1. Block diagram of the proposed methodology.

to the individual's initial position for avoiding premature convergence and augmenting the efficacy. For initializing the cheetahs' position, a cube map is wielded since it could generate enhanced uniformity variables.

Where, extracted features F_m are considered as the number of cheetahs, and the position of i^{th} the cheetah $F_{i,j}$ is initialized using a cube map and is represented as,

$$F_{i,j} = \frac{1}{2(B_u - B_l)} C_{i,j} + \frac{1}{2(B_u + B_l)} \; where, \; j = 1, 2, 3, \ldots d \tag{3}$$

where, B_u and B_l implies the upper and lower boundary of solution space, respectively, $C_{i,j}$ signifies a chaotic sequence, and denotes dimension. Here, to select the CHs, the node parameters, such as residual energy, Node degree, Centrality, Received Signal Strength (RSS), Position of the BS, and the remaining energy of nodes are considered as the fitness function.

a) Searching
Scanning mode is preferable while the prey is dense as well as grazing whilst walking on the plains. Selecting an active mode, which requisites more energy when analogized to the scan mode is better if the prey is scattered as well as active. Thus, during hunting, the cheetah might choose a chain of these '2' search modes. To update the cheetah i novel position in each arrangement employing Laplace distribution, the subsequent random search equivalence is presented grounded on their present position along with arbitrary step size.

$$F_{i,j}^{\tau+1} = e_1 + e_2 F_{i,j}^{\tau} \tag{4}$$

where, $F_{i,j}^{\tau+1}$ and $F_{i,j}^{\tau}$ implies cheetahs'i next along with the current positions in arrangement j, e_1 and e_2 signifies the scale parameter.

b) Hiding
Here, Cheetahs might sit as well as wait for the prey to come closer or else to improve once the prey has been detected. This is represented as follows:

$$F_{i,j}^{\tau+1} = F_{i,j}^{\tau} \tag{5}$$

c) Attacking
By employing '2' critical factors like speed and flexibility, cheetahs attack their prey. Cheetah charges at full speed toward the prey while it decides to attack. Then, the prey becomes aware of the cheetah's attack as well as starts to flee. The cheetah's attacking tactics

are equated as,

$$F_{i,j}^{\tau+1} = P_j^\tau + \overset{\vee}{R} \bullet \hbar_{i,j}^\tau \tag{6}$$

where, P_j^τ represents prey's current position, $\overset{\vee}{R}$ and $\hbar_{i,j}^\tau$ denotes the turning as well as interaction factor. Like the hunting process, CHs are selected to proceed with the further process of clustering, and selected CHs are denoted as F_{mH}.

5) CLUSTERING

Here, by employing DBKNN, the clustering is performed on selected CH. Grounded on the similarities betwixt the data points, the grouping process is conducted in KNN. Nevertheless, clustering with KNN becomes extremely slow when there are a large number of SNs. Thus, in general KNN, the Euclidean distance calculation is replaced by the Davies-Bouldin measure, which calculates the distance between each node faster and improves the speed of the existing KNN.

The selected CHs F_{mH} are taken as input. Next, select the number K of the neighbors in a random manner. Calculate the distance between the K numbers of neighbors by using the Davies-Bouldin index, which is given by,

$$\text{Dist} = \frac{1}{K} \sum_{i=1}^{K} \max_{i \neq \ell} \frac{\rho_i + \rho_\ell}{D(\rho_i - \rho_\ell)} \tag{7}$$

Here, Dist implies the distance, $\rho_i \in F_{mH}$ and ρ_ℓ signifies CH and node, and D delineates the distance between CH and node. Next, the node is assigned to that class for which neighbor is minimum. Ultimately, various clusters are formed based on the CH by using KNN. The engendered clusters (C) are mathematically expressed as,

$$C = \{C_1, C_2, \ldots\ldots, C_\wp\} \tag{8}$$

Here, $C_\wp$ implies $\wp^{\text{th}}$ number of clusters.

6) WEIGHT ASSIGNMENT

The clustering phase is followed by the assignment of weights to each CHs. The weights will be determined grounded on the energy engendered at the BS and the distance between it and the selected CH. The CHs after assigning the weights C^* are expressed as,

$$C^* = \left\{C_1^*, C_2^*, \ldots\ldots, C_\wp^*\right\} \tag{9}$$

Here, $C_\wp^*$ implies $\wp^{\text{th}}$ number of the cluster with the weight assigned CH.

7) RELAY NODE SELECTION

By employing AI-GTBO, relay nodes are chosen from once completed the weight assignment. For attracting attract opposite sexes to mate as well as its protective strategy of deploying a sort of anal fork for detecting predators, GTBO imitates the golden tortoise beetle's behaviour of changing colours. After the beetle's dual attractiveness along with survival strategy, the algorithm is modelled for generating novel solutions for the optimization problem. Nevertheless, a few demerits like overcrowding of random flights' search area and disruption owing to its lengthy search steps are available in the traditional GTBO. Thus, for calculating switching color, the paper proposes an adaptive function.

In AI-GTBO, the problem variables are signified by a position matrix as,

$$C^* == \begin{bmatrix} C_{1,1}{}^* & C_{1,2}{}^* & \cdots & C_{1,L}{}^* \\ C_{2,1}* & C_{2,2}{}^* & \cdots & C_{2,L}{}^* \\ \vdots & \vdots & \ddots & \vdots \\ C_{\diamond,1}{}^* & C_{b,2}{}^* & \cdots & C_{\Leftrightarrow,L}{}^* \end{bmatrix} \tag{10}$$

where, the entire clusters are signified as $\wp$ as well as the number of variables is delineated as L.

The fitness of each CHs is obtained by considering the Energy, distance, and density of nodes in that cluster. The fitness function is described as,

$$f(C) = f\left(\begin{bmatrix} C_{1,1}{}^* & C_{1,2}{}^* & \cdots & C_{1,L}{}^* \\ C_{2,1}{}^* & C_{2,2}{}^* & \cdots & C_{2,L}{}^* \\ \vdots & \vdots & \ddots & \vdots \\ C_{b,1}{}^* & C_{b,2}{}^* & \cdots & C_{b,L}{}^* \end{bmatrix}\right) \tag{11}$$

Here, each cluster's fitness value is depicted as $f(C)$. A random operator is deployed by AI-GTBO for initializing the 1st cluster. Grounded on the issue's lower together with upper bounds, the population members are prepared.

$$C_{x,1}^\varsigma = C_{\min}^\varsigma + \text{rand} * \left(C_{up}^\varsigma - C_{\text{low}}^y\right), \tag{12}$$

where, $\varsigma = 1, 2, \ldots, \alpha, y = 1, 2, \ldots, \beta$

Here, $C_{x,y}$ signifies the initial value of y^{th} variable of the x^{th} beetle, C_{low} and C_{up} delineates lower and upper bounds, implies the random number of range [0,1], y is the value of the x^{th} beetle, also, ς and α elucidates dimensions, and β denotes the total number of variables. The mature beetle solutions are now obtained by the expression,

$$C_x^g = C_x^g + \wp * \left(C_{r_i}^g - C_{best}^g\right) \tag{13}$$

Here, C_x^g denotes the female beetle's position in the generation g, which drives toward the golden male beetle $C_{r_i}^g$. The male beetle's golden color is obtained by the color-changing operator wp, r_1 and C_{best}^g specify a random integer in [1,∇] as well as a solution with the best fitness function at generation g. For mating with the golden male and producing offspring, the female position shifts. The following expression defines the color-switching operator υ using the adaptive function:

$$\upsilon = \frac{\phi}{\omega}\left(\frac{\sigma}{\omega}\right) e^{-(\sigma/\omega)} \tag{14}$$

where, ϕ, ω and σ implies values of parameters in a Weibull probability distribution function.

Due to the effectiveness of their predator-frightening defensive strategies, some of the eggs laid by beetles survive.

In AI-GTBO, to generate the remaining beetles, a crossover operator is used. It is expressed in the following ways:

$$C_1 = T \cdot C_{r_1} + (1 - T) \cdot \left(C_{r_2} - \gamma_1\right) \tag{15}$$

$$C_2 = T \cdot C_{r_2} + (1 - T) \cdot \left(C_{r_1} - \gamma_2\right) \tag{16}$$

Here, T implies a random number, and C_{r_1} and C_{r_2} signifies two randomly chosen solutions in the range of $[1,\nabla]$. The terms γ_1 and γ_2 are defined by the expressions,

$$\gamma_1 = (1 - O) \cdot \left(C_{\text{best}} - C_{r_1}\right) \tag{17}$$

$$\gamma_2 = (1 - O) \cdot \left(C_{\text{best}} - C_{r_2}\right) \tag{18}$$

Here, C_{best} and O imply the best solution obtained and crossover operator. In the end, the algorithm iterates, and while it gratifies the stopping condition, it fuses matured beetles' population with the survived beetles as well as picks the best solution. Hence, using the AI-GTBO algorithm, the relay nodes (C_{best}) for all clusters are selected. The pseudo code of the proposed AI-GTBO is depicted in Algorithm 1.

Algorithm 1 Input: Weight Assigned Clustered Nodes C^*
Output: Selected Relay Nodes C_{best}

procedure
Begin
  Initialize the population C^*, fitness function $f(C)$ and number of iterations
  Generate the position matrix
  Calculate the fitness value based on the five parameters
  Initialize population members
  for $i = 1$ to $\wp$ **do**
    while $i = 1$ **do**
      if $\left(C^{\zeta}_{x,1} > C^{g}_{\text{best}}\right)$ **then**
        {
        Update position of the female beetle
        }
      else
        {
        Sustain in same position
        }
      end if
    end while
    Compute the two solutions by the expressions,
    Store the solution in survival population
  end for
  Sort the solution based on the fitness value and select the best one.
  Return CHs
  end

8) PATH CREATION

Here, the path is created since it is the prominent phase to be performed before the shortest path is created. Thus, multiple paths are created between the nodes and BS. Next, the created path is denoted as $\vartheta \in C_{\text{best}}, \aleph_n$.

9) SHORTEST PATH CREATION

After creating the multiple paths between nodes and BS, for reducing the transmission time, the shortest paths are chosen using Dijkstra's algorithm in which the source vertex is assumed as 0, and the distance to all other vertices is infinity. Next, by connecting the intermediate nodes, the distance as of the source node to BS is measured. Until obtaining the shortest path by changing the connection between the node and BS, this same process of possibility is continued. Next, the created shortest path is denoted as ϑ_{shot}. In the end, the network is ready to transmit the data.

10) DATA UTILIZATION

This phase explains the utilization of data through the efficiently constructed network and they are explained in the following steps.

11) DATA SENSING

The number of SNs deployed in collaboration to form a network capable of reporting to data collection. Here, SNs are sensing information and directly transmitting it through the WSN. After carrying out the following steps, the transmission is finished with the BS. Here, the sensed data is initialized as,

$$\delta^z = \left\{\delta^1, \delta^2, \delta^3, \ldots . \delta^z\right\} \text{ where } a = 1, 2, 3, \ldots Z \tag{19}$$

where, δ^z denotes the sensor data.

12) CORRELATION ANALYSIS

Here, to compute correlation analysis between each data, Pearson Correlation Coefficient (PCC) is used for eradicating the redundant information from nodes. A statistical method used to measure the strength of the linear relationship between data obtained from two different nodes and compute their association is termed the PCC. Next, the linear relationship is derived as,

$$\mu^q = \frac{z\left(\sum (\delta^a)(\delta^a)^a\right) - \left(\sum \delta^a\right)\left(\sum \delta^a\right)^a}{\sqrt{\left[\sum \delta^{2a} - \left(\sum \delta^a\right)^2\right) \sum\sum \delta^{2a} - \left(\sum \delta^a\right)^{2a}}} \tag{20}$$

where, μ^q and imply correlation and number of sensed data, respectively, $\sum(\delta^a)$ and $\sum(\delta^a)^*$ delineates the sum of the two data, and $\left(\sum \delta^a\right)^2$ and $\left(\sum \delta^a\right)^{**}$ signifies the sum of the square of two individual data.

13) REDUNDANT NODE DETECTION

This phase detects the redundant nodes that provide repeated data when compared to other nodes. With the help of the Radial-Adaptive Neuro Fuzzy Interference (Radial-ANFIS) model, the detection is done by considering correlated values as input, which predicts the node to be kept active and sleep based on the correlation measure. Usually, a powerful model for computation, as well as prediction engendered by fusing the fuzzy Sugeno model with an adaptive neural network system, is termed Adaptive Neuro-Fuzzy Interference (ANFIS). Using the input from the previous layer, the firing strength in ANFIS is calculated. This calculation complicates the network and results in a gradient vanishing problem. To compute the firing strength, a Radial Basis Function (RBF) kernel is used to reduce computational complexity and improve network performance. In Figure 2, the proposed Radial-ANFIS architecture is shown.

Here, the fuzzification process is executed by the second layer and the nodes in this layer are adaptive nodes. The fuzzified output Ψ_i is,

$$\Psi_i = \mu_1 \left(\Omega_{w_h}\right) \tag{21}$$

$$\Psi_i = \mu_2 \left(\Omega_{w_v}\right) \tag{22}$$

Here, μ_1 *and* μ_2 implies input nodes, W_h and W_v signifies weight value, and Ω represents membership function (layer1).

In the third layer, output signals obtained from previous layers are multiplied and the output of the second layer ϖ_i is

$$\varpi_i = \mu_1 \left(\Omega_{w_h}\right) * \mu_2 \left(\Omega_{w_v}\right) \tag{23}$$

The rule's firing strength is signified by node output. By employing RBF, output described as normalized firing strength $(\varpi_i)^*$ is equated in the 4th layer.

$$(\varpi_i)^* = \sum \Omega_{W_h} \zeta \left(\mu_2 \left(\Omega_{W_v}\right) \varpi_i\right) + B \tag{24}$$

where, ζ and B implies kernel and bias. The fuzzy rule's consequent part is executed by the 4th layer. Here, the nodes are adaptive nodes. Node function is equated as,

$$(\bar{\varpi}_i)^* = (\varpi_l)^* (\phi_i \mu_1 + A_i \mu_2 + L_i) \tag{25}$$

Here, ϕ_i, A_i and L_i imply linear adaptive parameters, and $(\bar{\varpi}_i)^*$ signify defuzzification. In the end, the last layer predicts the output of whether the node is to be active or sleep and it is represented as,

$$\Gamma = \sum (\varpi_i)^* (\phi_i \mu_1 + A_i \mu_2 + L_i) \tag{26}$$

where, Γ is the overall outcome of the detection model. The redundant nodes are kept in sleep mode by this detection. For transmission, the remaining node data are utilized. The active node data is denoted as δ^z_{active}.

14) DIMENSIONALITY REDUCTION

Here, by employing Newton Raphson Iterative Principal Component Analysis (NRI-PCA), the dimensionality of the transmitted data from the node is reduced. A multivariate methodology, which analyzes data for extracting significant information, is termed the PCA. However, the conventional PCA is challenging for analyzing the covariance matrix precisely; also, unless the information is explicitly provided, it fails to capture the simplest invariance. Thus, to mitigate the aforesaid issue, Newton Raphson Iterative principle is adopted in the proposed work.

The pseudo code of the proposed Radial-ANFIS is depicted in Algorithm 2. Where q implies the total number of correlated values, and signifies a specified correlated value.

Algorithm 2 Input: Correlated Values
Output: Redundant Node

procedure
Begin
  Initialize Parameters Ψ_i, ϖ_i, W_h, W_v
  Compute Membership function of input
  Calculate the fitness value based on the five parameters
  Initialize population members
  for $i = 1$ to q **do**
    while $i = 1$ **do**
      Evaluate fuzzification
      Update weight value to layer 3
      $\varpi_i = \mu_1 \left(\Omega_{w_h}\right) * \mu_2 \left(\Omega_{w_v}\right)$
      Normalize the data obtained from layer 3
      Update bias and Kernal
      Execute the consequent part of the fuzzy rules $(\bar{\varpi}_i)^* = (\varpi_l)^* (\phi_i \mu_1 + A_i \mu_2 + L_i)$
    end while
  end for
  Summing all the output
End Begin
Return redundant node

Step1: Determine the sample mean of the Z-dimensional data set δ^z_{active}.

$$\Phi = \frac{1}{Z} \sum_{a=1}^{Z} \delta^z_{\text{actine}} \tag{27}$$

Here, Φ denotes obtained sample mean, Z represents the total number of data.

Step 2: Estimate the sample set's covariance matrix $\Im$ employing Newton Raphson Iterative principle.

$$\Im = \Phi - \frac{\text{fun}(\Phi)}{\text{fun}^*(\Phi)} \tag{28}$$

where, $fun(\Phi)$ and $fun^*(\Phi)$ implies the first and second derivatives of Φ.

Step 3: Estimate the sample covariance matrix's feature values l_I and feature vectors l_J.

$$\Im = Q^* \Sigma \cdot Q^T \tag{29}$$

where, feature matrix with corresponding feature vectors are signified as Q, Q^T is the transpose of Q, and Σ implies arranged diagonal matrix of feature values.

Step 4: Estimate the 1st row principal elements' cumulative variance contribution rate V_cum deploying the acquired feature values as well as feature vectors.

$$V_{cum} = \frac{\sum_{J=1}^{G} l_J}{\sum_{I=1}^{H} l_I} \tag{30}$$

Here, and implies the total number of feature values as well as feature vectors. Similarly, for all the row principal elements, the cumulative variance contribution rate is estimated.

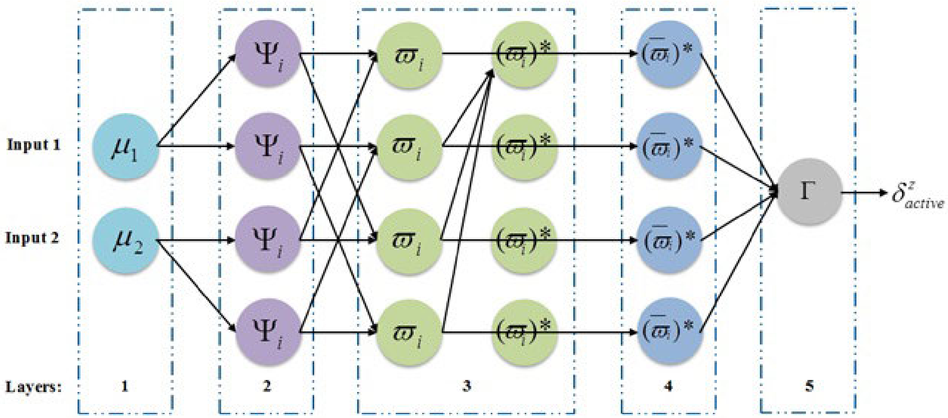

FIGURE 2. The architecture of the proposed Radial-ANFIS.

TABLE 1. Experimental parameters.

Parameters	Values
Number of Nodes	250
Network Size	250*250 m^2
Initial Energy	2J
Data Packet Size	5000 bits
Control Packet Size	100 bits
Sensing Radius	25m
Transmission Range	35m
Constant Bit Rate	500 kbps

Step 5: Deploy the obtained row feature vector for performing dimension reduction.

$$\Re = V_{\text{cum}} \cdot \delta^z_{\text{active}} \tag{31}$$

where, implies transformed data after reduction. Then, through the CH, relay node, and shortest path, the data is transferred to the BS. The data received at the BS comprises the EC of each SN during each iteration. Hence, the energy drop of each node can be monitored, and then to improve the network lifetime, the active and sleep status of nodes can be altered. In the end, the proposed framework's performance is analyzed by comparing it with some of the existing models and they are shown in the following phases.

IV. RESULT AND DISCUSSION

Here, the proposed technique's performance is evaluated with the available schemes. In the working platform of PYTHON, the proposed energy-efficient data transmission network is deployed. The experimental parameters used in the proposed model are shown in table 1,

1) PERFORMANCE EVALUATION OF PROPOSED RADIAL-ANFIS

The proposed techniques' performance is appraised with the available ANFIS, Artificial Neural Network (ANN), Support Vector Machine (SVM), together with Random Forest (RF) for proving the proposed model's superiority.

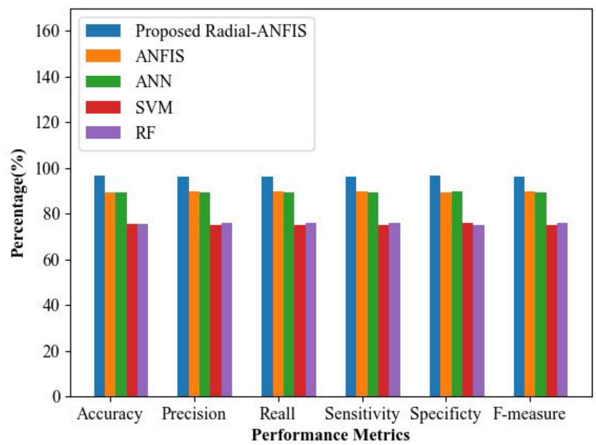

FIGURE 3. Graphical representation of proposed and existing methods.

In Figure 3, regarding accuracy, precision, recall, sensitivity, specificity, and F-measure, the proposed technique's performance is evaluated with the traditional systems. Accuracy is used to quantify how good the model is at detecting sleep and active nodes accurately from the total 250 nodes. Sensitivity refers to a test's ability to designate an individual node as sleep or active. Specificity reports the presence or absence of a condition. Precision and recall quantify the number of positive class predictions that actually belong to the positive class. F-measure combines the precision and recall scores of a model. The system's better performance is depicted by higher metric values. The proposed methodologies' accuracy is 96.49%, which is higher than the accuracy of ANFIS and ANN, which are at 89.47%, and SVM and RF, which are at 75.43%.The proposed method has the same precision, recall, sensitivity, and F-measure achieved 96.42%. Similarly, the specificity of the recommended model is 96.55%. Thus, the proposed method is highly efficient than the traditional models. The potential performance is mainly due to the learning ability of

TABLE 2. Training time analysis.

Method	Training Time
Proposed Radial-ANFIS	6009.662
ANFIS	10014.93
ANN	13079.79
SVM	16009.49
RF	18014.32

TABLE 3. Network life time.

No.of Nodes	Proposed LCCOA	CO	BOA	SMOA	CSOA
50	9652	8425	7523	6359	5142
100	10458	9632	8632	7485	6358
150	11254	10245	9471	8659	7485
200	12854	11478	10523	9321	8652
250	13954	12325	11478	10457	9358

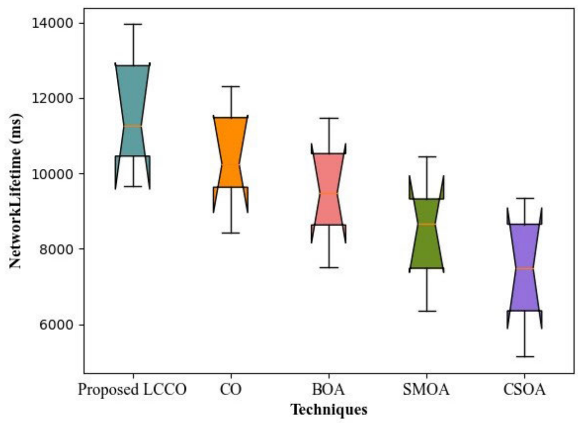

FIGURE 4. Graphical representation of average Network Life time for the proposed and existing models.

the RBF function. The RBF technique imposed a non-linear separable function to understand the patterns in the data in high dimensions. Thus, there is an improvement in accuracy as input dimensionality increases.

The representation of the computational time analysis is depicted in Table 2. Computation time is the process of the execution time of classification, which is exhibited in Table 2. When analogized to the RNN and other available techniques, which has slow and complex training procedure, the proposed one executes its process rapidly due to the inducement of the Radial Basis function. The proposed method reduces computational time by 4,005.268ms compared to the existing ANFIS, 7,070.128ms compared to the ANN, and 12,004.658ms compared to the RF by using the proposed method. Therefore, the learning ability of RBF to approximate linear combinations of training data reduced the proposed model's training time. Hence, the proposed model has higher efficacy than the existing methods.

2) PERFORMANCE EVALUATION OF PROPOSED LCCO

Here, the proposed LCCOA's performance is analyzed to the existing techniques, namely CO, Butterfly Optimization Algorithm (BOA), Sequential minimal optimization Algorithm (SMOA), and Cat swarm optimization Algorithm (CSOA).

The lifetime of the proposed LCCOA and existing methods are illustrated in Table 3 and Figure 4. The LCCOA has a life time of 9652ms while 50 nodes are used for data transmission. This is 1227ms improved than existing CO, and 2129ms improved than existing BOA. Similarly, the life time of the proposed model is 10458ms for using 100 nodes and compared with the traditional methods. Hence, the energy-efficient operations of CH selection, multiple path creation and path selection, and selecting the relay node had a major influence on enhancing network lifetime. It ensured the higher efficacy of the developed model.

In Figure 5(a), the performance analysis centered on the packet loss ratio is exhibited. The lower loss value represents the efficient performance of the developed model. In the proposed model, it takes 8.3256% of loss when using 50 nodes, and 7.3564% of loss when using 100 nodes. These are lower than the existing model.

In Figure 5(b), the performance analysis grounded on the packet delivery ratio is depicted. The higher delivery value

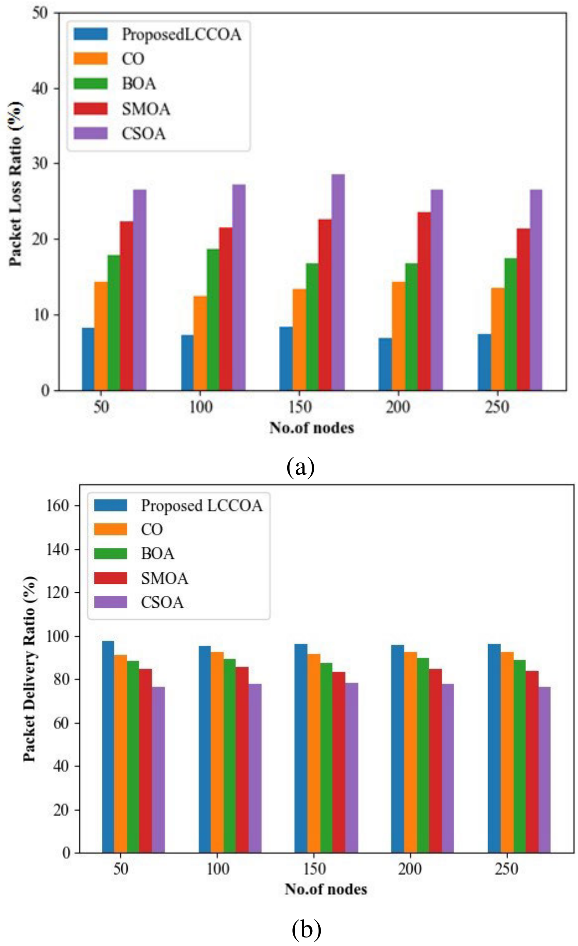

FIGURE 5. Graphical representation of proposed and existing methods (a) packet loss ratio (PLR) (b) packet delivery ratio (PDR).

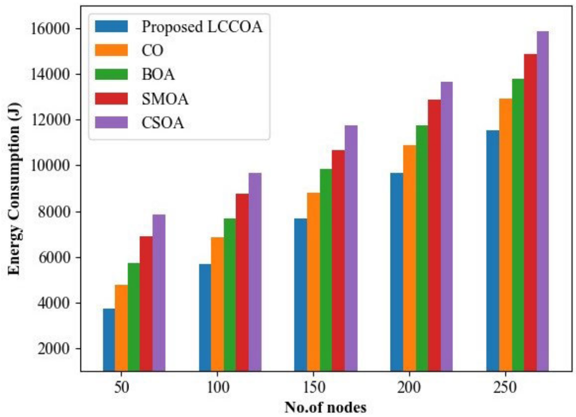

FIGURE 6. Energy consumption analysis.

represents the efficient performance of the developed model. Thus, the proposed model's packet delivery when using 50 nodes is 97.5275%, 95.4471% when using 100 nodes, and 96.3255% when using 150 nodes. These are also greater than the current model. However, the shortest path creation was the potential for high PDR and low PLR of the proposed model, where the unwanted overhead in data transmission is less due to the shortest path.

The EC analysis under the circumstances of data transmission and reception is exhibited in Figure 6. Each task consumes a power consumption amount for a period of time. Thus, energy consumed by the proposed methodology when using 50 nodes is 3748J, 5692J for 100 nodes, and 7684J for 150 nodes. The reason for the minimum EC of the proposed model is that eliminating redundant data helped in energy saving as most of the energy of the node gets wasted in dealing with the redundant data transmission. Thus, the higher performance of the developed model can be proved.

Figure 7 analyses the performance of the proposed and existing methods in terms of (a) bandwidth delay, (b) latency, and (c) jitter. When the node count is 250, the minimum delay of the proposed method is 2143ms, the latency of the proposed model is lower with 8798ms, and the jitter is only 0.001943s than the existing methods. This performance improvement of the proposed model is guaranteed by the effective use of CH selection, redundant node detection, and shortest path computation.

Figure 8 compares the throughput of the proposed and existing CH selection methods. When the sensor nodes range from 200 to 250 nodes, the throughput attained by the proposed model varies from 6749Bps to 7214Bps. But, the throughput attained by the existing methods is lower than the proposed model. This potential performance of the proposed model is mainly due to the improved exploitation degree imposed by the LC technique over the selection of CH on the network.

In Figure 9, the computational time of the proposed model is compared with the existing CO, BOA, SMOA, and CSOA algorithms. When weighted against the existing CO method, the computation time of the proposed model is less

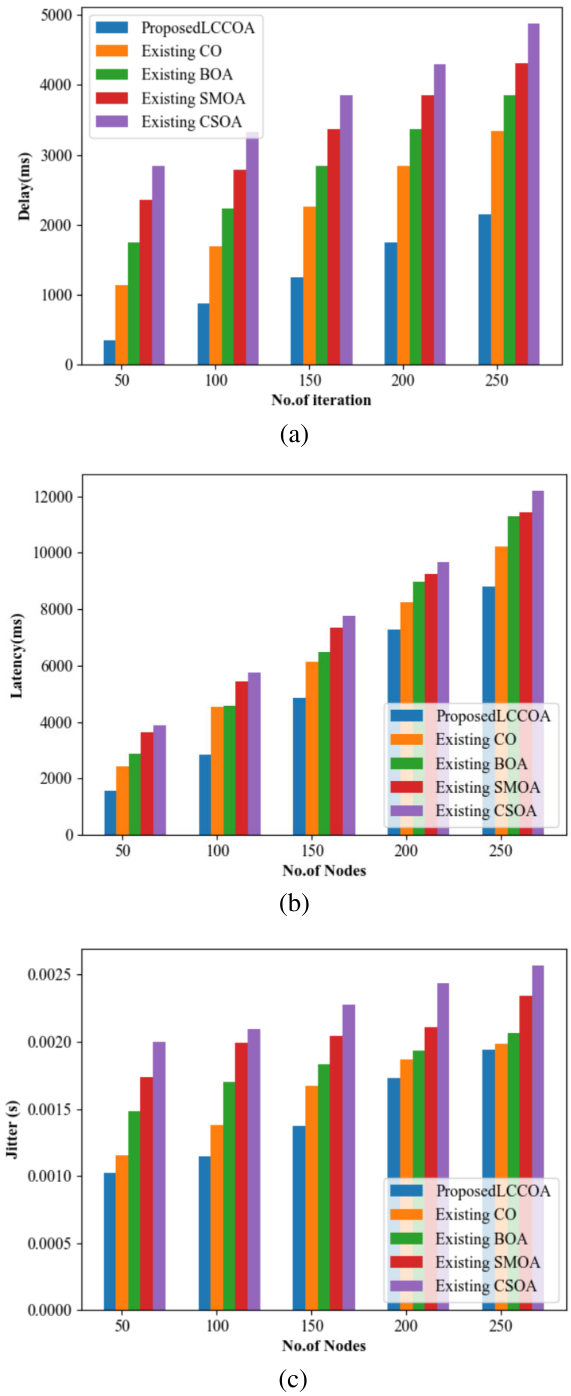

FIGURE 7. Performance analysis (a) Delay (b) Latency (c) Jitter.

by 1782 ms for 250 nodes. The computation cost of the proposed model is lower than the existing methods. Hence, by balancing the data transmission and reception in WSN, the proposed model made the network energy highly stable since the data transmission from redundant nodes is neglected.

3) PERFORMANCE ANALYSIS OF THE PROPOSED DBKNN

Here, the clustering execution of the proposed is analogized to the prevailing KNN, Partition Around Medoids (PAM), K-Means Algorithm (KMA), and Fuzzy C Means (FCM).

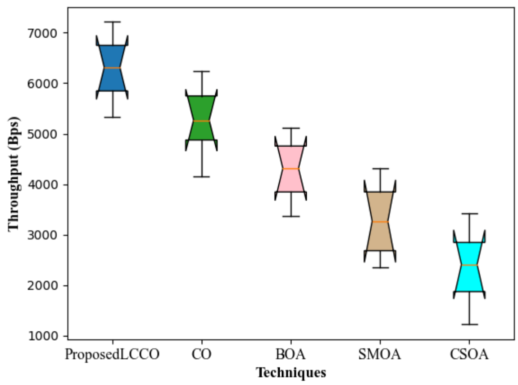

FIGURE 8. Throughput analysis.

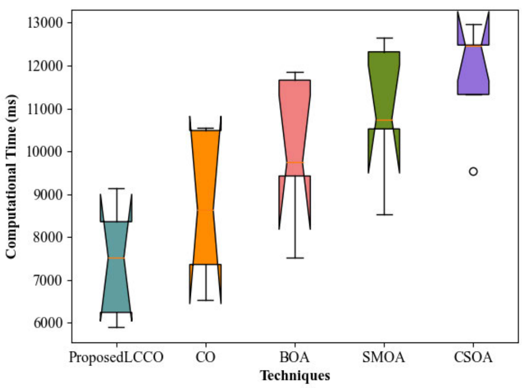

FIGURE 9. Complexity analysis.

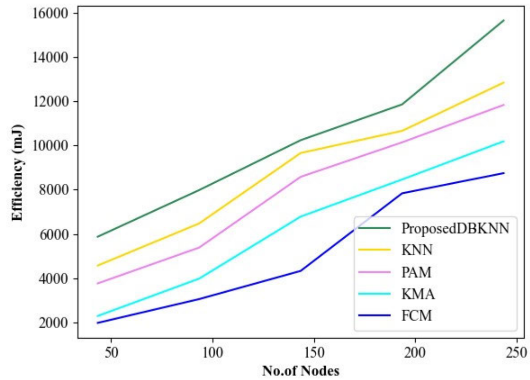

FIGURE 10. Performance comparison of proposed DBKNN.

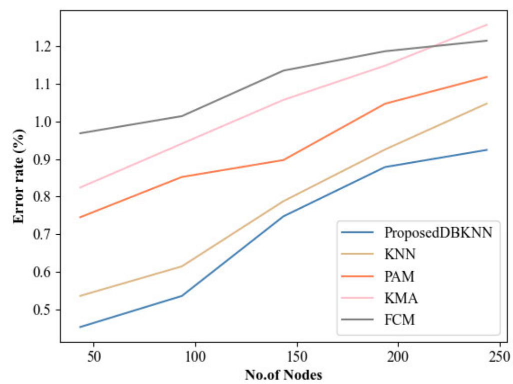

FIGURE 11. Error rate analysis.

TABLE 4. Clustering time analysis.

No. of Nodes	Proposed DBKNN	KNN	PAM	KMA	FCM
50	2415	3596	4258	5237	6295
100	3586	4857	5328	6932	8541
150	4875	5986	7914	8245	10254
200	5682	8213	10523	11478	12854
250	5983	10457	11478	12325	13954

Regarding clustering time, the proposed system is evaluated with the prevailing ones in Table 4. Better system performance will be attained by taking minimum time. Clustered time of the proposed model is 2415ms for 50 nodes, which is 1171ms lower than existing KNN, 2, 460ms lower than PAM, and 3267ms lower than KMA. Moreover, by employing different counts of nodes, the proposed as well as existing methods are analogized. Thus, the proposed one is highly superior to all other conventional methods. This indicates that the computation of Davies-Bouldin gave better separation between nodes when the nodes are arbitrarily shaped with a dispersed density.

Figure 10 analyses the efficiency of the proposed DBKNN and existing KNN, PAM, KMA, and FCM methods to cluster the nodes. When nodes vary from 50 to 250, the efficiency of the proposed model to cluster the nodes was improved by 1303mJ for 50 nodes, 1507mJ for 100 nodes, 578mJ for 150 nodes, 1195mJ for 200 nodes, and 2808mJ for 250 nodes. On the other hand, the conventional KNN attains 4572mJ to cluster 50 nodes, which is very low compared to the proposed DBKNN to cluster 50 nodes (5875mJ). Similarly, for the remaining number of nodes and other existing techniques, the efficiency of clustering the varying number of nodes is very low. By comparing these values, it is clear that the proposed DBKNN attains higher efficiency than the existing techniques. Thus, the incorporation of the Davies-Bouldin technique to compute the distance between CH and other nodes speeds up the process resulting in improved efficiency.

Figure 11 shows the error rate calculated between the sum of squared distances among data points and their assigned cluster centroids for the proposed and existing clustering techniques. By considering 150 nodes, the error attained by the proposed method is 0.7475, which is less than the existing methods. Thus, the minimum error rate attained by the proposed model demonstrates the goodness of separation between clusters using the Davies-Bouldin method.

4) PERFORMANCE ANALYSIS BASED ON OBJECTIVES

Here, the proposed LCCOA's performance while employing 100 nodes is weighed against Energy-Efficient Protocol (EEP), Global artificial Bee colony algorithm centered on

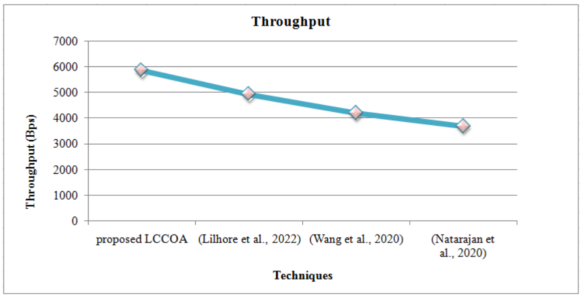

FIGURE 12. Performance analysis of the proposed method with the existing method.

the Crossover and Tabu Search (GABCTS), and Piezoelectric method with Multicast Particle Swarm Optimization (PM-PSO). The proposed technique's performance is contrasted with the prevailing schemes centered on throughput in Figure 12. The throughput within a certain distance of the proposed LCCOA is 5847, which is higher than all other existing methods. It can only be attained by proposing the Laplace distribution for avoiding uniform distribution. In the end, when analogized to the prevailing techniques, the proposed system's overall performance is superior. Although the existing methods showed significant performance improvement, they were inefficient due to redundant data transmission, randomized CH selection, and high dimensional data transmission. But, in the proposed model, the CH selection based on sensor node features, relay node selection for energy efficient data gathering, redundant node detection to save nodes energy and lifetime, and dimensionality reduction are incorporated to provide feasibility for energy-constrained WSN. The model reduced the randomization in CH selection, which can affect network scalability. It provides detection of redundant nodes, thus reducing the redundant data transmission by the adjacent node and EC of the network along with increasing the network's longevity. Another resourceful algorithm to select a relay node is proposed for sensor information gathering. Although the cluster head communication betwixt diverse clusters is highly efficient, it fails to choose the nodes with low energy in the case of larger networks. Hence, it is more advantageous in the sense that it effectively reduces the energy dissipation in transferring data by aggregating all the data from the CHs and sending it to the BS in large-scale networks. In general, SNs have low initial energy, and transferring high dimensional data always causes a large amount of EC. This has been trounced by the effective dimensionality reduction technique to transform higher dimensional data into the lower dimension, thereby saving the energy consumed by the nodes during data transmission. These advances in WSN have led to the feasibility of implementing an energy-constrained network.

V. CONCLUSION

Here, energy-efficient data transmission is proposed in WSN. Node initialization, portioning, feature extraction, CH selection, clustering, relay node selection, shortest path creation, data sensing, correlation analysis, redundant node detection, and dimensionality reduction are performed by the proposed method. After executing all the steps, the simulation analysis is performed in which the performance of the proposed Radial-ANFIS and LCCO was analyzed and compared with the existing techniques. As per the final outcome, the proposed model attains an accuracy of 96.49% and the EC is 3748J for 50 nodes. Likewise, for all other metrics, namely sensitivity, specificity, precision, recall, f-measure, PDR, PLR, EC, and Network lifetime, the proposed model achieves the best result. Thus, when weighed against the prevailing methodologies, the proposed model is highly efficient. The proposed effort was primarily concerned with minimizing the node's EC by choosing the shortest route; no precautions were taken to guard against packet attacks or ensure secure transmission. WSNs are used in numerous applications that involve sensitive information, which needs to be secure and confidential. Also, the mobility of the network is not focused, which is important for the growing number of nodes to connect and exchange messages in WSN. The work will be done using extremely sophisticated procedures in the future to solve security issues in WSNs and allow nodes to have freedom of movement.

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