



Energy Efficient Evolutionary Algorithm based Clustering with Route Selection Protocol for IoT Assisted Wireless Sensor Networks

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Abstract – Internet of Things (IoT) assisted wireless sensor network (WSN) finds its applicability in several real-time tracking and surveillance applications. However, it suffers from various issues such as restricted battery capacity, repeated interruptions owing to multi-hop data transmission, and limited communication range. Gathering and multihop directing are considered effective solutions to complete enhanced energy competence and a generation of IoT-assisted WSN. An NP-hard problematic that can be handled with an evolutionary algorithm is the collection of the cluster head (CH) and the best potential paths to the goal. Both of these problems involve finding the optimum route to the target (EA). In this context, this study presents the design of the Energy Efficient Evolutionary Algorithm-based Clustering with Route Selection (EEEE-CRS) Protocol for Internet of Things-Assisted Wireless Sensor Networks (IoT-Assisted WSN). The EEEA-CRS technique that has been proposed has the primary intention of enhancing the energy efficiency as well as the lifetime of the IoT-assisted WSN. The EEEA-CRS approach that has been presented is broken down into its basic parts, which are the Fuzzy Chicken Swarm Optimization based Clustering (FCSO-C) phase and the Biogeography Optimization-based Multihop Routing phase (BBO-MHR). The FCSO-C technique that has been suggested chooses CHs with the use of a fitness function that takes into account residual energy, inter-cluster distance, and intra-cluster detachment. In adding, the BBO-MHR strategy identifies the optimum pathways to BS by taking into account the costs of communicating with other clusters, both within and between them. A number of different simulations were carried out in order to demonstrate that the EEEA-CRS methodology yields superior results. The EEEA-CRS method was shown to be

superior to other methods in use today, according to the findings of an exhaustive comparison and study.

Index Terms – Internet of Things, Wireless Sensor Networks, Evolutionary Algorithm, Energy Efficiency, Clustering, Multi-hop Routing.

1. INTRODUCTION

The Internet of Things, shortened as "IoT," is a way of describing how the Internet is associated to the corporeal world. When it was first developed, its capabilities were restricted to radio frequency identification (RFID), but it has since advanced to the point where those limitations are no longer an issue [1]. It has established an ideal direction for many applications, protocols, and domains, as well as excellent directions for different systems, services, and devices. The forward-thinking ideas of cloud computing and big data can be traced back to this development. But academics have been concerned about the limitations of the internet of things ever since it was introduced [2]. One problem that could not be overlooked was the fact that the constraints of the Internet of Things (IoT) continue to be a significant barrier to the spread of the IoT, particularly for sensor networks. Common uses of wireless sensor networks (WSN) include monitoring of the human body, the marine environment, and mines. Because a battery provides electricity to each node in a WSN, the overall lifetime of the network has a finite amount of time [3]. Routing protocols are an essential component of the underlying technology that underpins WSNs. In this approach, the energy of the node is

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frequently lost in the mechanism that is responsible for the data connection, and the node's overall power consumption is not consistent. As a result, the most critical part of the routing model is balancing and reducing the amount of power that is consumed by the network.

The WSN-enabled Internet of Things network is deployed over a wider area than the WSN network; in the same vein as WSN networks, there is frequently a large number of nodes (typically as a result of space restrictions) [4]. Because of this, it is possible that the typical WSN approach will not perform effectively in an IoT network that is supported by WSN and can adapt. The clustering-based routing protocol's principal goals are to organize and select the CH that will provide the remaining cluster node with the highest level of efficiency. Within the groups, a node conveys its information to CH. The CHs are accountable for local cluster member info meeting and transmission the collected info to the neighboring CH/ BS. The CH has high energy losses than expected. It performs as a further burden on the CH when compared to standard nodes [5]. To avoid trouble and extend the network lifetime, effectual energy consumption is widely considered.

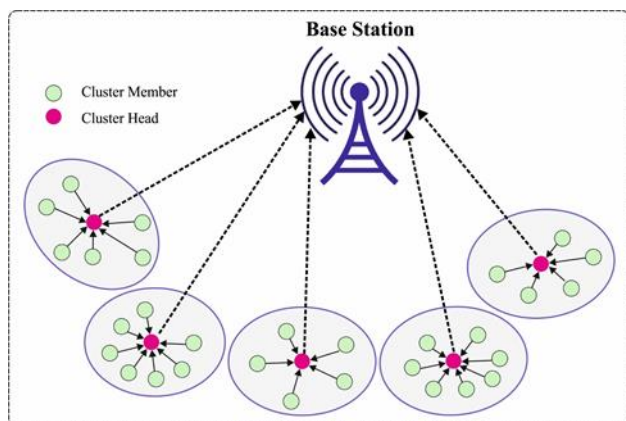


Figure 1 Structure of Clustered IoT Assisted WSN

Utilizing multihop routing in conjunction with clustering is the standard method to enhancing the energy efficiency of a network. This is one of the most common methods. [6] In order to prevent the majority of network nodes from being able to direct their information to the base position in a direct connection, these network nodes are grouped together into groups. A CH node will be chosen to represent each cluster on the basis of the specifications that have been supplied. Before sending the processed data to the BS through multihop through another CH node, the CH nodes would first receive data from another cluster member node. Only then would they transmit the data to the BS. This strategy has two substantial benefits over others that cannot be ignored. To get things started, the CH node in the cluster could compress the information that it has acquired from the other nodes in the

cluster in order to eliminate any redundant information that isn't necessary. The energy efficiency of the network is significantly improved by allowing each network node to forward to neighbouring CH nodes and confining multihop transmission to only CH nodes [7, 8]. Because of this, the number of network nodes that are able to participate in multihop transmission is greatly increased. Figure 1 illustrates the architecture of a wireless device network that is clustered and is supported by the Internet of Things.

The remaining parts of the paper are prepared in the subsequent method: A review of the relevant literature is presented in Section 2. In Section 3, background information are provided. An in-depth description of the suggested procedure is discussed in section 4. In Section 5, we will talk about how to implement the recommended strategy as well as evaluate its effectiveness. The conclusion is included in Section 6 of the paper.

2. RELATED WORKS

The quality of service (QoS) based QOECR strategy for Internet of Things-based wireless sensor networks that was proposed by Rishiwal et al. [9] is evaluated. The projected model identifies the best route for sink nodes and provides the best possible choice for sub-sink nodes. The RCBRP method was presented by Shafiq et al. [10] in order to determine the routing path that uses the least amount of energy in instruction to lengthen the lifespan of the system. The energy ingesting and distance computation method, on the one hand, and the energy-efficient routing and clustering methodology, on the other, are the two methods that are presented. In their paper [11], Mahajan et al. developed a new approach to Cross-layer Clustering (NICC) that is based on a Nature-Inspired technique. They create NICC in order to research efficient routing and clustering solutions for SF applications and then implement such solutions. In addition, a BFO technique should be provided for choosing the best sensor for routing and clustering issues based on cross-layer features and the fitness value computation.

Mahajan, H.B et al. [12] developed a new routing method-based ant colony optimization (ACO) model for multi-agents that handles network resources sufficiently in a real-time scenario. The presented model discovers the following destination of ant and handles evaporation rate and pheromone update operator. This technique considered some major parameters like barrier size, remaining energy, distance, and traffic rate while selecting the following destination underneath separate scenarios. Seema, B et al. [27] This information program between the SNs and the BS demands the expenditure of energy on everyone's part. Because of potential energy loss caused by a variety of variables, the amount of energy that is utilized is frequently more than the amount of energy that is actually required. The transmission of redundant data is an illustration of a component that

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contributes to the waste of energy. Seyyedabbasi, A et al. Using the evolutionary computing based on genetic algorithms (OptiGACHS) method, the network's efficiency in utilizing its available energy can be increased. Incorporating characteristics such as the possible for heterogeneous nodes to create fitness function, distance, and density, the providing technique offers an improved CH election process. Optimization for CH election has as its primary goal lowering power consumption. Furthermore, it is anticipated that optimal CH selection for energy-efficient routing is a non-deterministic process.

This is an NP-hard problem. However, CH does not seem to care. The incorporated meta-heuristics used to optimize the election process offers a wide range of health and fitness benefits. An energy efficiency problem in WSNs is addressed by the CSO clustering method. As an upgrade to CSO, CSO uses the genetic algorithm's procedures in CSO to improve it. Individuals with a low fitness value are targeted by CSO-crossover GA's and mutation processes, which increases the variety of the population.

An Energy Efficient Evolutionary Algorithm-based Clustering with Route Selection (EEEE-CRS) Protocol for Internet of Things-Assisted Wireless Sensor Networks is discussed in this article. The EEEA-CRS approach that has been presented is broken down into its basic parts, which are the Fuzzy Chicken Swarm Optimization based Clustering (FCSO-C) phase and the Biogeography Optimization-based Multihop Routing phase (BBO-MHR). The suggested FCSC-C technique selects CHs based on the FF method by making use of intra-cluster detachment, residual energy, and inter-cluster distance. On the other hand, the BBO-MHR technique determines the most efficient routes to the BS by taking into account both the intra-cluster and the inter-cluster communication costs.

In order to illustrate the improved energy-effective outcomes produced by the EEEA-CRS algorithm, a number of experiments have to be carried out. Utilizing the CSO fit feature is a great way to cut down on energy consumption while also striking a balance between several service quality measures. Simulation of a wireless sensor network (WSN) and analysis of the suggested approach, based on significant criteria in the field of radio device networks.

3. BACKGROUND INFORMATION

This section offers a detailed explanation of the network model and energy model involved in this study. Some assumptions involved in this work are given as follows [14]:

- The network is homogeneous based on sensing range, storage, and battery level.
- When the network is functional, IoT nodes and BS are inactive.

- The distance between two nodes is computed using the receive signal strength index as the basis for the calculation (RSSI).
- Once the energy of the IoT node is consumed, it implies dead status, and its battery is fully drained.
- IoT nodes are arbitrarily placed over the target region, considered as $100 \times 100 \text{m}^2$.
- The battery is non-rechargeable or irreplaceable.
- There is no limitation for BS based on storage and processing.

The radio energy model is useful in decreasing the energy utilization of the network, i.e., employed in aggregation, sensing, transmission, and amplification. In receiving and transmitting s bits, the amount of energy dissipated is shown below equation (1) and equation (2).

$$E_{TX}(S, d) = \begin{cases} sE_{elec} + s\epsilon_{fs}d^2, & d < d_0 \\ sE_{elec} + s\epsilon_{mp}d^4, & d > d_0 \end{cases}, \quad (1)$$

$$E_{RX}(S) = E_{RX-elec}(s) = sE_{elec}, \quad (2)$$

whereas E_{RX} represent the energy needed for the greeting of moments of information, E_{TX} indicates the energy consumed to transmit information, d denotes the departure among receiver and spreader, d_0 indicates a edge which defines multipath/free space model adapted, also ϵ_{fs} and ϵ_{amp} represent the coefficient of amplification as shown in the equation (3).

$$d_0 = \sqrt{(\epsilon_{fs}/\epsilon_{amp})} \quad (3)$$

Let's say that E_{DA} stands for the amount of energy that is consumed during information aggregation. The following formula is used to calculate the dissipation energy for nodes that are not connected to a CH. In this formula, d CH stands for the distance that separates the node from its CH as shown in equation (4) and equation(5).

$$E_{CH}(S) = ns(E_{elec} + \epsilon_{fs}d_{CM} + E_{DA}), \quad (4)$$

$$E_{CM}(S) = s(E_{elec} + \epsilon_{fs}d_{CM}), \quad (5)$$

where E_{elec} indicates the energy consumed for moving individual data bit.

4. THE PROPOSED MODEL

In this study, a unique EEEA-CRS protocol was developed with the goal of achieving the highest possible level of energy efficiency in IoT-Assisted WSN. Constructing clusters on the basis of FCSC-C and choosing routes on the basis of BBO-MHR are both components of the EEEA-CRS technique that has been offered. In the beginning, the FCSC-C approach is

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utilized so that CHs and structural clusters can be selected. After that, in the second stage, the BBO-MHR method was applied in order to figure out which communication routes between clusters were the most effective. The EEEA-CRS method's overarching workflow is depicted in its entirety in Figure 2.

4.1. Design of FCSO-C Technique for Cluster Construction

Primarily, the nodes in the IoT-assisted WSN are arbitrarily placed in the target area and the initialization process is performed. Then, the FCSO-C technique is applied to organize clusters and choose CHs. The CSO method consists of chicks, roosters, and hens, all of them have distinct behavior specifications [15]. Some of the basic assumptions for the CSO method is given in the following:

- This method splits a chicken swarm into several groups, all of them have a small number of chicks, one rooster, and several hens.

- The identity of chicks, roosters, and hens is defined by the fitness value, the worst one is the chick, the optimal one is elected as rooster, and the remaining are the hens.
- In the entire population, the mother-children's relationship, the individual identity, and the spouse relationship remain the same for G generation (G represent the iteration cycle), and the mother-children relationship, the spouse relationship, and the identity would be upgraded afterward G generation.
- In all the groups of an entire population, a hen follows their spouse rooster for finding food, and they would arbitrarily compete for food with another member in a group. The individual with optimal fitness value is highly possible to attain foods.

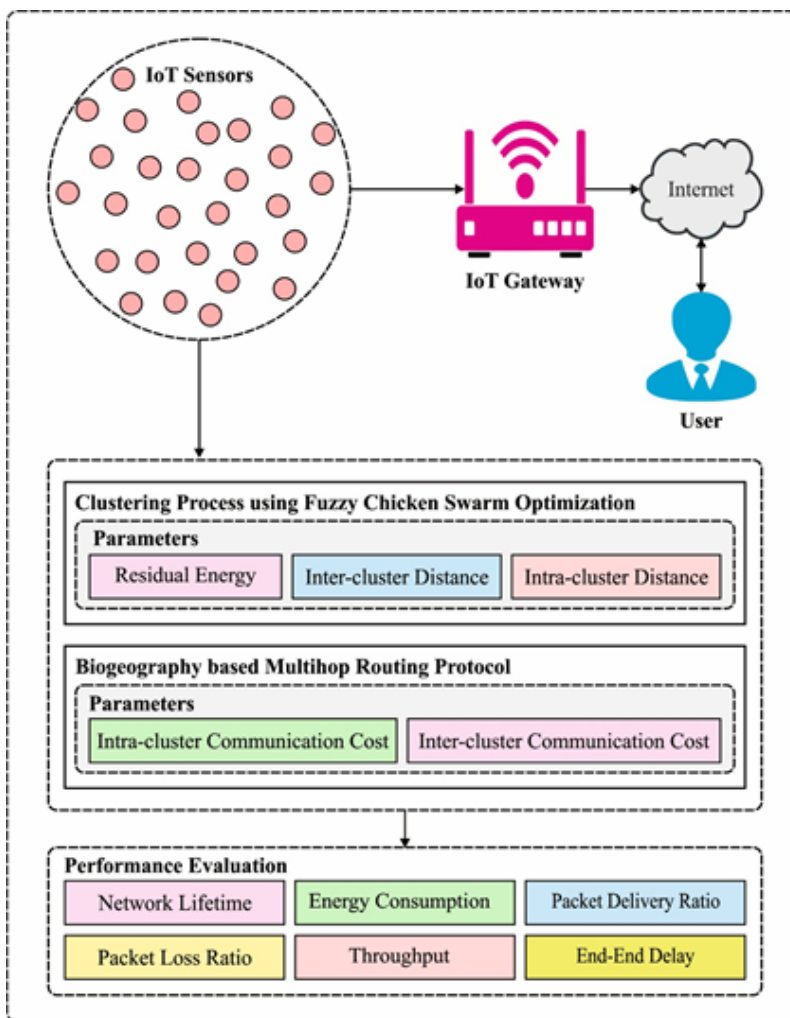


Figure 2 Block Diagram of EEEA-CRS Protocol

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All the chickens are defined by their location. Here, MN, RN, HN, and CN represents the number of mother hens, roosters, hens, and chicks correspondingly, also $x_{i,j}^t$ denotes the location of i^{th} chicken in j^{th} measurement space on the t^{th} repetition, in which T , N , and D , $t \in \{1, \dots, T\}$, and $i \in \{1, \dots, N\}$, $j \in \{1, \dots, D\}$ represents the maximum iteration times, the overall amount of chickens, and the dimension number correspondingly. A rooster, a chick, and a hen have their certain location updating formula. For a rooster, its recurring location can be determined by below equation (6) and equation (7):

$$x_{i,j}^{t+1} = x_{i,j}^t * (1 + Randn(0, \sigma^2)) \tag{6}$$

$$\sigma^2 = \begin{cases} 1, & \text{if } f_i \leq f_k, \\ \exp\left(\frac{f_k - f_i}{|f_i| + \varepsilon}\right), & \text{otherwise } k \in [1, RN], k \neq i. \end{cases} \tag{7}$$

Now, $Randn(0, \sigma^2)$ indicates an arbitrary value follow Gaussian distribution with a variance of σ^2 and expectation of zero, ε represent a smaller constant, k denotes the quantity of other roosters i.e., arbitrarily selected, and f_i and f_k indicates the fitness value of i^{th} and k^{th} roosters, correspondingly [16]. The recurring location of a hen can be described by the below equation (8), equation (9) and equation (10).

$$x_{i,j}^{t+1} = x_{i,j}^t + C_1 * Rand * (x_{r_1,j}^t - x_{i,j}^t) + C_2 * Rand * (x_{r_2,j}^t - x_{i,j}^t) \tag{8}$$

$$C_1 = \exp\left(\frac{f_i - f_{r_1}}{abs(f_i) + \varepsilon}\right) \tag{9}$$

$$C_2 = \exp(f_{r_2} - f_i) \tag{10}$$

Now, C_1 and C_2 denotes the learning factor, $Rand$ represent an arbitrary value following uniform distribution within $[0,1]$, r_1 represent the directory of rooster i.e., the spouse of i^{th} hen, r_2 denotes the quantity of rooster or hen i.e., chosen arbitrarily, and $r_1 \neq r_2$. The recurring location of a chick can be determined by using equation(11):

$$x_{i,j}^{t+1} = x_{i,j}^t + FL * (x_{m,j}^t - x_{i,j}^t) \tag{11}$$

whereas $x_{m,j}^t$ denotes the mother hen of chick and FL denotes an arbitrary issue in the possibility of $[0,2]$.

In order to intuitively represent human knowledge based on the manipulation of a parameter in order to achieve high accuracy and convergence, adopting the fuzzy model is predicated on the concept of applying the fuzzy concept to the parameter alteration of the CSO technique. This is the fundamental idea that lies behind the adoption of the fuzzy model. To put it another way, the value of the parameter ought to be ambiguous so that the knowledge-based evaluation of how to alter the parameter can take place. After the fuzzy value of the parameter has been defuzzified, the

process can continue to be carried out. The presented method adapts the fuzzy method for adaptively adjusting the parameter of CSO under distinct population scenarios.

The FCSO method adapts the fuzzy method to alter the quantity of chickens and chance factors adoptively, as well the adapted unsure method contains 4 mechanisms, involving a fuzzy rule base, fuzzifier, fuzzy inference engine, and defuzzifier. The input parameter to the fuzzy method is chicken aggregation, optimization speed, and iteration times that is fuzzified by the Gaussian fuzzifier. The input variable is extracted for monitoring the running state of the presented method, involving aggregation of chickens, iteration times, and optimization speed. The output variable is made up of three components: the number of chickens, denoted by N ; the random variable, denoted by $Rand$; and the function, denoted by FL . This output variable is then sent to CSO in order to regulator its operation, and the enhanced monitoring indicator (or input variable) is then inputted iteratively to the fuzzy approach in order to adaptively alter the CSO restriction in order to circumvent the constraints imposed by the CSO method [17].

The proposed Energy Efficient Evolutionary Algorithm-based Clustering with Route Selection (EEEE-CRS) describe as the following steps

steps:

Step 1: Set aggregation, sensing, transmission, and amplification variables.

Step 2: Find the $E_{RX}(S)$ from the energy consumed to transmit information, d denotes the departure among receiver and spreader, edge which defines multipath/free space model adapted and coefficient of amplification.

Step 3: Find CH, the quantity of energy used in an iteration

Step 4: calculate $E_{CM}(S) = s(E_{elec} + e_{fsd_CM})$.

Step 5: Find the *Fitness function* based on ntracluster nodal distance to that of their respective CHs.

Step 6: Optimal route selection using BBO-MHR.

The FCSO-C technique is centrally controlled at the BS/sink which would be a node provided with higher energy. This presented method-based gathering would function in iteration where each iteration is initiated by the setup stage in which cluster formation takes place [18]. Once this phase initiates all the nodes it would transmit data present state of energy and the location of the BS. To ensure that, the node with the adequate number of energies is selected to be CH the node has an energy equal that is over the unkind would last as the CH for the iteration. The following BS would run the presented method to determine the optimal m CHs which might decrease fitness function. The cluster distance, the round in

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which the first and last nodes pass away, and the fitness function are the three parameters that make up the fitness function. By shortening the distance that separates the nodes in the network, this strategy tries to spread the area of the system. On the other hand, the communication at the CHs is improved as a consequence of the transmission of data concerning residual energy to the base station (BS) (BS).

Fitness function

$$= \varepsilon_1 \times f_1 + \varepsilon_2 \times f_2 + \varepsilon_3 \times f_3 \tag{12}$$

In which $\varepsilon_1 + \varepsilon_2 + \varepsilon_3 = 1$ and $0 < \varepsilon_1, \varepsilon_2, \varepsilon_3 < 1$

Let f_1 be the intracluster nodal distance to that of their respective CHs and l_j signifies the node belongs to the CH_k . The f_2 the function would be the reciprocal of CH whole power and their candidate in the existing iteration. The f_3 function would represent a ratio of the average sink distance to the total number of nodes in the network. The value of weight $\varepsilon_1, \varepsilon_2, \varepsilon_3$ are determined as the user and employed to control 3 objective functions. The fitness function i.e., abovementioned would have the target to increase the intracluster distance which presents in-between the node, and sequentially the CHs are computed by f_1 , which improves the energy efficacy of this network since it is denoted as f_2 and additionally, minimize the average sink distance f_3 . As shown in the above equation (13-15)

$$f_1 = \sum_{k=1}^m \frac{1}{l_j} \left(\sum_{i=1}^{l_j} dist(S_j, CH_k) \right) \tag{13}$$

$$f_2 = \frac{1}{\sum_{j=1}^m E(CH_j)} \tag{14}$$

$$f_3 = \frac{\frac{1}{m} \sum_{j=1}^m dist(CH_j, BS)}{N} \tag{15}$$

4.2. Design of BBO-MHR Technique for Optimal Route Selection

Throughout the course of the routing process, the best possible choice of routes is arrived at by applying the BBO-MHR methodology. Biogeography is the education of the topographical distribution of different species of living organisms. In BBO, every possible solution to a problem is considered to be a "habitat" by the application of the habitat survival index (HSI) [19], which is analogous to the capability of EA to assess an individual's level of fitness. The lower and higher HSI habitats are identical in terms of their characteristics. The migration mechanism that allows data to be exchanged between solutions is being modified by BBO [20]. The evolutionary process might be able to maintain more accurate information on individuals in order to ensure

that population convergence occurs. Employing a mutation function to generate one-of-a-kind solutions is one way to boost the diversity of a population.

If we assume that the total number of individuals in a species is S then we can use the equation to get both the species' migration rate, which is signified by λ_i and its emigration rate, which is denoted by μ_i . in the below equation(16):

$$\lambda_i = I \left(1 - \frac{S_i}{S_{max}} \right), \mu_i = \frac{E S_i}{S_{max}} \tag{16}$$

where S_{max} represent the most species quantity of each habitation. E and I indicate the maximalization of emigration and migration rates, correspondingly. When it comes to migration functions, the individual rates of emigration and immigration are what are employed to assess whether or not the feature values of one solution need to be swapped out for those of another solution[21]. It would be ideal to find a solution that has a low rate of emigration but a high rate of immigration. Through the utilization of this movement, the solution that has the largest rate of immigration likes to share data with the solution that has the highest rate of emigration. The solution that has a larger emigration rate will accept many of the characteristics of the solution that has a higher immigration rate[22]. BBO displays a stronger capability for exploitation in the searching space by making use of migration. If we make the assumption that the number of species changes over time as a result of migration, we can use the equation P_s to get an approximation of the likelihood that the habitat contains species S . Subsequently, the m_i mutation rate can be determined by Equation. (17-19).

$$\dot{P} = \{ ((\lambda_s + \mu_s)(\lambda_s + \mu_s P_s + \lambda_{s-1} P_{s-1} + \mu_{s+1} P_{s+1}) + \mu_{s+1} P_{s+1} P_{s+\lambda_{s-1} P_{s-1}} S = 0, \tag{17}$$

$$P_s = \begin{cases} -(\lambda_s + \mu_s)P_s + \mu_{s+1}P_{s+1}, S = 0, \\ -(\lambda_s + \mu_s)P_s + \lambda_{s-1}P_{s-1} + \mu_{s+1}P_{s+1}, 1 \leq S < S_{max} - 1 \\ -(\lambda_s + \mu_s)P_s + \lambda_{s-1}P_{s-1}, S = S_{max}. \end{cases} \tag{18}$$

$$m_i = P_{mute} \left(1 - \frac{P_i}{P_{max}} \right) \tag{19}$$

In which P_{mute} represent a predetermined variable, P_i is evaluated by (6), and $P_{max} = \max_{1 \leq i \leq N} \{P_i\}$. The mutation function is executed according to m_i . Solutions with lower probability P_i is possible to mutate another solution[23]. On the other hand, some solution with higher P_i have the small possibility to mutate. With this mutation function, different solutions are generated.

The routing issue is treated as a multi-objective minimized issue. During this case, 2 purposes are regarded as for

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improving the data distribution reliabilities. The objective of the BBO-MHR technique is to minimize the costs of intra-cluster as well as inter-cluster transmissions [24]. The objective function of the BBO-MHR technique is given as follow equation (20-21).

$$\sum_{k=1}^{|V|} \sum_{m=1}^{|c_k|} W_{cm_{m,k} \rightarrow CH_k} \tag{20}$$

$$\sum_{k=1}^{|V|} W_{CH_k \rightarrow NextHop_{CH_k}} \tag{21}$$

where, $CH_k \rightarrow CH$ number k ; $k \rightarrow$ Entire amount of chosen CHs; $NextHop_{CH_k} \rightarrow$ Next hop to CH_k ; $cm_{m,k} \rightarrow$ Cluster member number m of clusters k ; $V \rightarrow$ The vector including the chosen CHs; $C_k \rightarrow$ The vector covers the CM from the cluster that equivalent to CH_k . as shown in equation(21).

5. EXPERIMENTAL VALIDATION

5.1. Environmental Setup

In order to put the suggested procedure into action, the wireless sensor network (WSN) must first be established by making use of the settings that are considered to be standard. The environment now features the functioning version of the proposed network. The application of this scenario requires the use of the tool MATLAB 2021a, which is needed to carry out the process of putting it into action [25]. Examining the characteristics of the intended network's other parameters can also help one decide the initial setup of the WSN. In order to analyses the impact that heterogeneous nodes have on the performance of clustering methods, the following simulation metrics will be investigated.

- **Node Death Rate:** In order to put the suggested procedure into action, it is necessary to first construct the wireless sensor network (WSN) by utilizing the settings that are regarded as being standard[26]. Only then can the procedure be put into action. The environment at this point already contains a fully operational version of the envisioned network. The process of putting this scenario into action requires the use of the programmed MATLAB 2021a, which is required to carry out the necessary steps in order to complete the procedure. The initial configuration of the WSN can be determined with a little bit of aid from looking at the characteristics of the other parameters of the proposed network. The following simulation metrics will be studied in order to analyze the effect that heterogeneous nodes have on the performance of clustering algorithms[27]. This will be done so in order to better understand the implications of using heterogeneous nodes.

- **Network Lifetime** refers to the duration of time during which a network is actively operating. First Node Death

(FND), Half Node Death (HND), and Remaining Nodes are the three stages of a network's existence that are distinguished by the value 21. (HND). The various simulation parameters are listed in table 1.

Table 1 Simulation Parameters

Network dimension	100 x 100
Number of sensor nodes	100
Coordinate of the sink node	(50,50)
Initial energy of the nodes	0.5J
Initial energy of the sink node	50J 5X10 ⁸
Energy consumption of data transmission	5X10 ⁸
Energy consumption of data reception	1X10 ¹⁰
Energy consumption of routing packet transmission	13X10 ¹³
Energy consumption of routing packet reception	5X10 ⁹
Energy consumption of data aggregation	0.01
Initial probability of selecting the sensor node as the CH	3500
Maximum number of rounds	4000
Data packet length	10
Number of packet transmissions at each hop	100
Routing packet length	5000
Radio range	20 MHz

5.2. Performance Validation

The suggested EEEA-CRS method is put through its paces with varying numbers of IoT nodes in order to validate its level of performance. Table 2 provides a comparison between

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the EEEA-CRS technology and the approaches that are currently in use in rappings of the packet delivery ratio (PDR), the energy consumption (ECM), and the longevity of the network. [20, 21] (NLT)[28]. The ECM analysis of the EEEA-CRS approach is compared to other methods already in existence in Figure 3. According to the findings, the EEEA-CRS algorithm performed far better than any of the other techniques. If we take 100 IoT nodes as an example, the EEEA-CRS approach was able to reduce the ECM by 32.83 mJ, but the KHOA, GWOC, FEEC-IIR, and EETSP strategies were all able to increase the ECM by 148.88 mJ, 137.78 mJ, 68.22 mJ, and 59 mJ, respectively. The EEEA-CRS method achieved the lowest ECM value of 119.23mJ with 500 nodes, whereas the KHOA, GWOC, FEEC-IIR, and EETSP techniques achieved higher ECM values of 279.10mJ, 253.78mJ, 186.64mJ, and 170.63mJ, respectively. The EEEA-

CRS method also achieved the lowest ECM value of 119.23mJ with 500 nodes.

Figure 4 provides a quick introduction to the EEEA-CRS methodology and other PDR-related techniques. The figure described that the EEEA-CRS technique has achieved extreme presentation over the other ones [29]. For example, with 100 IoT nodes, the EEEA-CRS technique has obtained an extreme PDR of 99.78% whereas the KHOA, GWOC, FEEC-IIR, and EETSP systems have achieved minimum PDR of 94.81%, 97.01%, 99.34%, and 99.76% respectively. Moreover, with 500 IoT nodes, the EEEA-CRS model has gained an increased PDR of 99.78% in which the KHOA, GWOC, FEEC-IIR, and EETSP models have achieved minimum PDR of 86.54%, 90.17%, 94.53%, and 95.99% respectively.

Table 2 Comparative Results Analysis of EEEA-CRS Technique under Different Number of IoT Nodes

Energy Consumption (mJ)					
No. of IoT Nodes	KHOA	GWOC	FEEC-IIR	EETSP	EEEA-CRS
100	148.88	137.78	68.22	59.00	32.83
200	175.33	163.70	107.58	86.37	58.09
300	200.45	185.43	145.83	113.00	79.35
400	245.42	215.12	159.66	145.60	90.76
500	279.10	253.78	186.64	170.63	119.23
Packet Delivery Ratio (%)					
100	94.81	97.01	99.34	99.76	99.78
200	93.53	95.59	97.70	99.04	99.74
300	91.28	94.43	96.25	98.31	98.72
400	88.98	91.81	95.40	97.51	98.27
500	86.54	90.17	94.53	95.99	97.33
Network Lifetime (Rounds)					
100	4303	4525	4963	5232	5767
200	4131	4237	4834	5017	5662
300	3824	4006	4641	4928	5405
400	3430	3575	4336	4513	5115
500	3227	3221	4080	4327	4991

Figure 4 provides a brief assessment of the EEEA-CRS procedure and other techniques in terms of PDR. The graph designated that the EEEA-CRS method has reached the highest presentation associated to the others [30]. Using 100 IoT nodes as an illustration, the EEEA-CRS technique has achieved an extreme PDR of 99.78 percent, while the KHOA, GWOC, FEEC-IIR, and EETSP schemes have achieved

smallest PDRs of 94.81 percent, 97.01 percent, 99.34 percent, and 99.76 percent, correspondingly. In adding, with 500 IoT nodes, the EEEA-CRS model has improved its PDR to 99.78 percent, whilst the KHOA, GWOC, FEEC-IIR, and EETSP models have achieved minimum PDRs of 86.54 percent, 90.17 percent, 94.53 percent, and 95.99 percent, correspondingly.



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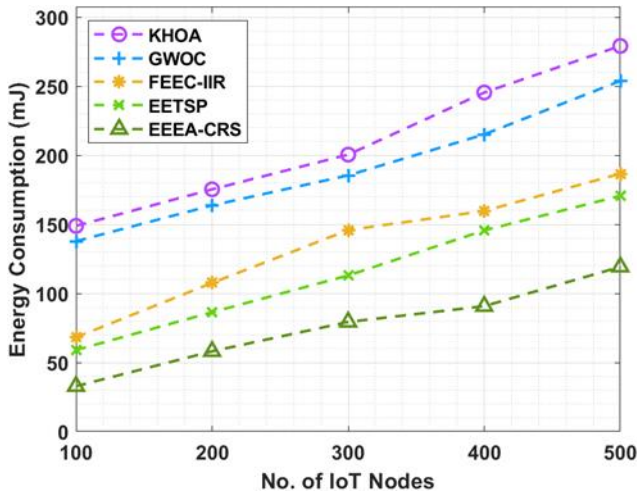


Figure 3 ECM Analysis of EEEA-CRS with Existing Techniques

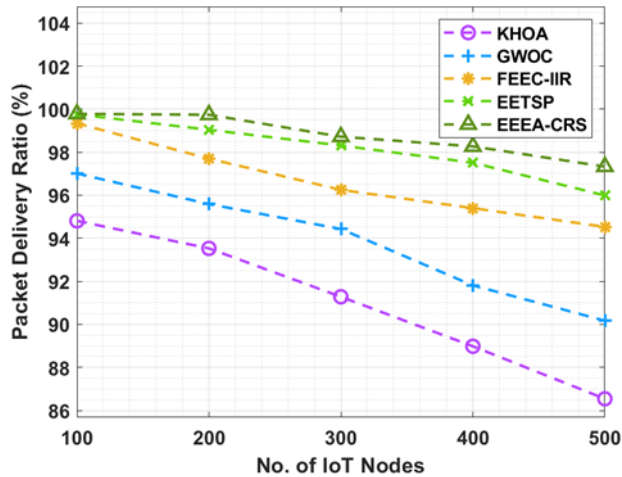


Figure 4 PDR Analysis of EEEA-CRS with Existing Techniques

A full comparison of the EEEA-CRS methodology and the approach taken by other NLT-related models is presented in Figure 5. According to the graph, the EEEA-CRS model has already achieved its highest possible level of efficiency in contrast to the other models [31]. The EEEA-CRS system, for example, has a higher NLT of 5767 rounds compared to the KHOA, GWOC, FEEC-IIR, and EETSP models, which have lower NLTs of 4303, 4525, 4928, and 5232 rounds, respectively, when using 100 IoT nodes. This is because the EEEA-CRS system is more complex. In addition, using 500 IoT nodes, the EEEA-CRS method obtained a superior NLT of 4991 rounds, whereas the KHOA, GWOC, FEEC-IIR, and EETSP algorithms obtained inferior NLTs of 3227, 3221, 4080, and 4327 rounds, respectively. The EEEA-CRS method also obtained a superior NLT when compared to its competitors.

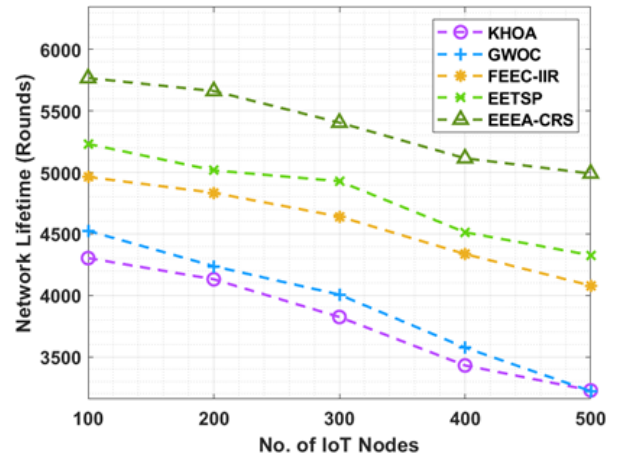


Figure 5 NLT Analysis of EEEA-CRS with Existing Techniques

Table 3 offers a proportional consequences examination of the EEEA-CRS technique with recent approaches concerning end to end delay (ETED), packet loss ratio (PLR), and quantity. Fig. 6 reviews the ETED of the EEEA-CRS method with current methods. The outcomes exhibited that the EEEA-CRS model has accomplished minimal EEEA-CRS method over the other algorithms. For example, with 100 IoT nodes, the EEEA-CRS model has resulted in minimal ETED of 0.89s whereas the KHOA, GWOC, FEEC-IIR, and EETSP approaches have gained superior ETED of 5.03s, 4.64s, 3.10s, and 1.72s correspondingly. Eventually, with 500 nodes, the EEEA-CRS approach accomplished the least ETED of 9.75s whereas the KHOA, GWOC, FEEC-IIR, and EETSP methods have attained increased ETED of 8.03s, 8.24s, 7.70s, and 3.15s correspondingly.

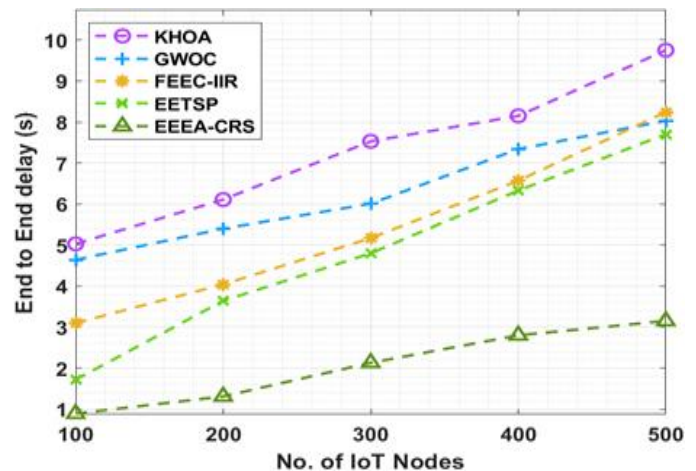


Figure 6 ETED Analysis of EEEA-CRS with Existing Techniques

A brief comparative study of the EEEA-CRS method and other models concerning throughput is provided in Figure 7.

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Table 2 Result Analysis of EEEA-CRS Technique with Existing Methods under Distinct Quantity of IoT Nodes

End to End Delay (s)					
No. of IoT Nodes	KHOA	GWOC	FEEC-IIR	EETSP	EEEA-CRS
100	5.03	4.64	3.10	1.72	0.89
200	6.11	5.40	4.04	3.64	1.31
300	7.53	6.01	5.17	4.80	2.13
400	8.15	7.34	6.57	6.33	2.80
500	9.75	8.03	8.24	7.70	3.15
Throughput (Mbps)					
100	0.75	0.86	0.91	0.97	0.98
200	0.69	0.81	0.79	0.83	0.93
300	0.57	0.62	0.72	0.82	0.87
400	0.49	0.60	0.64	0.68	0.72
500	0.42	0.56	0.52	0.60	0.76
Packet Loss Ratio (%)					
100	5.19	2.99	0.66	0.24	0.22
200	6.47	4.41	2.30	0.96	0.26
300	8.72	5.57	3.75	1.69	1.28
400	11.02	8.19	4.60	2.49	1.73
500	13.46	9.83	5.47	4.01	2.67

The number indicated that the EEEA-CRS model was more efficient than the others. Using 100 IoT nodes as an illustration, the EEEA-CRS methodology has obtained a maximum throughput of 0.98Mbps, whereas the KHOA, GWOC, FEEC-IIR, and EETSP techniques have achieved lesser throughputs of 0.75Mbps, 0.86Mbps, 0.91Mbps, and 0.97Mbps, individually. with 200 nodes, the EEEA-CRS methodology has reached maximal throughput of 0.93Mbps in which the KHOA, GWOC, FEEC-IIR, and EETSP techniques have achieved lower throughput of 0.69Mbps, 0.81Mbps, 0.79Mbps, and 0.83Mbps correspondingly. Equally, with 500 IoT nodes, the EEEA-CRS method has gained an increased throughput of 0.76Mbps while the KHOA, GWOC, FEEC-IIR, and EETSP systems have achieved reduced throughput of 0.42Mbps, 0.56Mbps, 0.52Mbps, and 0.60Mbps respectively.

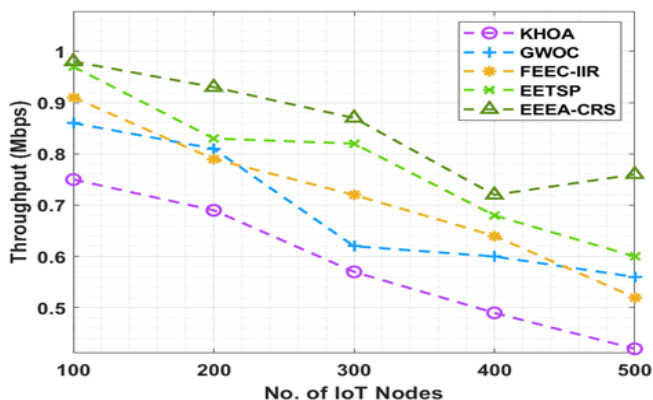


Figure 7 Throughput Analysis of EEEA-CRS with Existing Techniques

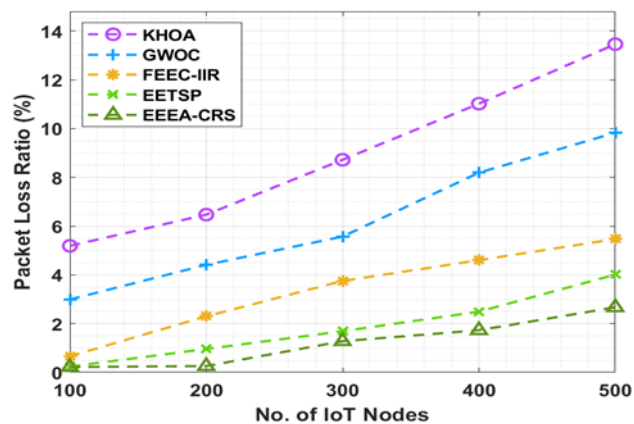


Figure 8. PLR Analysis of EEEA-CRS with Existing Techniques

Finally, Fig. 8 examines the PLR study of the EEEA-CRS algorithm with current methods. According to the findings, the EEEA-CRS strategy resulted in the creation of the most compact EEEA-CRS system when compared to the other strategies. The EEEA-CRS algorithm achieved a PLR decrease of 0.22 percent by using 100 IoT nodes as an example, whereas the KHOA, GWOC, FEEC-IIR, and EETSP techniques achieved PLR reductions of 5.19 percent, 2.99 percent, 0.66 percent, and 0.24 percent, respectively. The EEEA-CRS methodology achieved the lowest PLR of 2.67 percent with 500 nodes, in contrast to the KHOA, GWOC, FEEC-IIR, and EETSP strategies, which achieved PLRs of



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13.46 percent, 9.83 percent, 5.47 percent, and 4.01 percent, respectively. As can be seen from the graphs and data that have been shown so far, the implementation of the EEEA-CRS method has led to an increase in the IoT-assisted WSN's level of energy efficiency.

6. CONCLUSION

During the course of this training, a brand new EEEA-CRS procedure has been industrialized with the goal of obtaining extreme energy competency in IoT-Assisted WSN. The cluster formation method based on FCSO-C and the route selection method based on BBO-MHR are both components of the projected EEEA-CRS approach. The suggested FCSO-C technique chooses CHs based on a fitness function by utilizing intra-cluster detachment, residual energy, and inter-cluster distance. In addition, the BBO-MHR method selects the most optimal paths to the BS by taking into account both the intra-cluster and the inter-cluster transmission costs. A variety of tests were carried out in order to illustrate the enhanced energy effectiveness of the EEEA-CRS model. Additionally, a brief comparison study demonstrated the improved energy effectiveness of the EEEA-CRS algorithm in contrast to other techniques in terms of numerous metrics. In comparison to earlier methods, the EEEA-CRS algorithm has shown significant improvement in terms of the average amount of energy used, the rate at which data is delivered, and the longevity of the network. In the future, data aggregation and lightweight cryptographic techniques can be designed for IoT-assisted WSN.

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