IMPROVED SWARM BASED DISTRIBUTED ENERGY- EFFICIENT CLUSTERING PROTOCOL FOR IoT NETWORK USING HYBRID OPTIMIZATION METHOD

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DOI: 10.5281/zenodo.12662257

Abstract

A Smart City integrates various key elements, including technology, finance, government, and management, highlighting specific connectivity requirements. Wireless technologies such as ZigBee, Bluetooth, 4G, WiMax, Wi-Fi, and LTE have established themselves as solutions for communication in smart city initiatives. However, as the prevalence of unlicensed noise and bandwidth issues increases, IoT is being utilized to address these challenges. This article addresses the problems of resource allocation (RA) and routing by proposing an enhanced Swarm Distributed Energy-Efficient Clustering Scheme (ES-DEEC) protocol for IoT networks. This method, based on hybrid optimization techniques (PSO-GWO), focuses on data clustering and meta-heuristic approaches for optimizing IoT devices and gateway allocation. It also introduces a nature-inspired swarm optimization method for routing. The performance of the ES-DEEC method is demonstrated using MATLAB simulations, with experimental results compared to the existing ECRR method in terms of energy consumption (EC), Packet Delivery Ratio (PDR), network lifetime (NLT), and network throughput (TH).

Keywords: Enhanced Swarm Distributed Energy-Efficient Clustering Scheme (ES-DEEC), Particle Swarm Optimization (PSO), Grey Wolf Optimization (GWO), Internet of Things (IoT), Packet Delivery Rate (PDR), Network Lifetime (NLT).

1. INTRODUCTION

Nowadays, Wireless Sensor Networks (WSNs) represent a significant advancement in wireless technology. These networks utilize energy-restricted micro sensors and a Base Station (BS) source worldwide to ensure efficient data collection and management, promoting sustainability and longevity. A WSN comprises low-power, intelligent sensor nodes (SNs) connected by a high-power sink that adheres to specific transmission rules.

The Internet of Things (IoT) is a vital technology that has revolutionized various applications by providing a global, consistent network, which enables a more intelligent and pervasive world. In the context of ad hoc wireless technology, the IoT finds applications across diverse fields. WSNs have become an integral component of smart cities, using IoT environments to create intelligent devices that automatically send, receive, and share data within a limited area.

Future generations of WSNs aim to enhance connectivity, data throughput, and computational efficiency, while IoT and WSN devices are increasingly deployed in smart industries. However, IoT devices face challenges due to limited computational resources and energy, as they send sensor information to base stations for

ISSN 1462 2815

processing, underlining the need for further advancement. Efficient routing algorithms in WSNs can improve network efficiency.

The development of effective communication and routing protocols for WSNs/IoT encounters challenges such as the unreliability of low-power wireless networks and limited resources, often resulting in inadequate Quality-of-Service (QoS). The dynamic nature of WSNs renders traditional wireless channel and routing techniques unsuitable, limiting their application to basic routing requirements due to their high dynamic characteristics.

The IoT significantly aids humanity as a WSN by collecting, processing, and transferring data from hazardous environments to secure locations. Networks utilize small sensor nodes with rechargeable and interchangeable batteries, enhancing efficiency by effectively utilizing scarce resources.

Techniques to reduce energy consumption and boost network durability can improve WSN efficacy, as energy management affects sensor node longevity post-deployment.

Multilevel clustering is being developed as an energy-efficient data-gathering method to decrease node energy consumption and enhance network longevity in WSNs. IoT-based WSNs are fundamental in energy-constrained environments, requiring solutions for prolonged operation without battery replacements or location changes. The most energy-intensive tasks involve nodes performing data transmission.

Efficient routing protocols are crucial for optimizing data transfer in IoT-oriented WSNs while minimizing energy consumption. Despite numerous routing protocols ability to address issues of EE in IoT-oriented WSNs.

Hybrid optimization techniques have been employed to create an EE, congestion-aware resource allocation (RA), and RP for IoT networks, integrating software-defined networks into WSN [3].

The EE Congestion-Aware RA protocol utilizes data clustering (DC), meta-heuristic methods, and a queue-related swarm optimization tool for efficient large-scale device and gateway allocation. The technique is implemented and compared to existing techniques [4].

Resource allocation (RA) in the IoT network involves monitoring performance and configuring the network. The RA interfaces are typically located at the end of the network, providing relevant information to the device manager. IoT connects smart objects via the Internet, enabling communication between environments.

Routing is crucial in IoT networks, defining the effective route for data transmission and considering numerous factors like EC and network congestion (NC), for better operation and reliability.

The power consumption (PC) of forwarding nodes is affected by data routing, and stochastic methods are used to study PC and predict future behavior. However, major issues in IoT networks include energy, delay efficiency, and more life routing, as multiple real-world objects may perform the same task.

The routing for minimum power lossy networks is a new design to address the challenges of IoT routing, particularly in WSN. Network design faces challenges like node deployment, multiple devices, and various standards. IoT combines traditional networks, WSN, Zigbee, and WiFi using different protocol stacks.

Intermittent connectivity is risky due to limited battery life and mobile device disconnections. Multi-hop communication is crucial for low-powered devices, and fault tolerance (FT) is crucial for handling unexpected events. Context awareness computing uses context information to make necessary changes in routing processes [5].

Krishna Kumar et al. [6] proposed an EE link stable routing (EELSR) for intelligent devices to improve network lifetime (NLT) and minimize EC. This protocol was compared with Adhoc On-demand Distance Vector (AODV) and RP based on Energy and Link quality (REL) protocols, considering parameters.

The protocol addresses the limitations of smart devices like limited memory, processing power, and energy. *Daniel Godfrey et al. [3]* described an intelligent Energy Efficient Routing protocol (EERP) for IoT networks using the reinforcement learning (RL) method with dynamic objective selection (DOS).

Simulations show improved energy efficiency, faster network adaptation, enhanced PDR, and reduced data latency, addressing challenges like reliability and scalability. ***K. V. Praveen et al. [4]*** introduced an ECRR for IoT networks, utilizing crossbreed optimization methods and data clustering to mitigate congestion and compare it to existing methods.

Recently, IoT users have faced challenges in determining best-fit services for consumer needs and environmental targets, requiring effective routing methods to improve EC and NLT, despite the numerous devices.The main research work is described below:

1) To resolve RA and routing introduce an EE resource allocation-related issues and routing method (E-DEEC) using an optimized route selection technique (GWO-PSO) for IoT in WSN.
2) The Enhanced Swarm Distributed Energy-Efficient Clustering Scheme (ES-DEEC) is a research method that optimizes IoT device allocation, mitigates EC, and enhances network performance by efficiently managing data transmission.
3) The other main research work is to introduce swarm-based methods for choosing the best route based on numerous limitations that improve the path discovery structure.

The research article is managed in different sections. The literature review of the work is described in section 2. The main problem statement is discussed in the section 3. The research methodology and implemented methods are described in detail in section 4. The experiment result analysis and comparison analysis are done in Section 5. Section 6 defined the research work conclusion and future scope.

2. LITERATURE REVIEW

Zhaoming et al. (2020) [7] developed a model termed a dynamic routing (DR) algorithm based on EE relay selection (RS). The method enhanced a dynamic RA based on EE-RSs to accommodate sophisticated time-varying software-defined WSNs for IoT applications. The study investigates features of SDWSNs, calculates node state-transition probability using Markov chains, and designs a dynamic link weight for DRA-EE-RS and cost.

The EE routing problem was optimized using this method and determining the best relay based on EE-RS criteria. The simulation results were obtained by using Dijkstra's shortest path method for path EE, with a link weight coefficient. Sarvesh et al. (2023) [8]recommended a hybrid data RA based on a metaheuristic method for EE-WSN applications in the IoT. The authors utilized a swarm optimization and EE heuristic method in route finding to enhance data RAs for WSN.

The PSO method residual energy (RE) Stable Election Protocol (SEP) method provided a comprehensive solution for various performance parameters. The protocol enhances swarm search for efficient routing in EE cluster-based heterogeneous WSN.

That reduced cluster head CH selection cycle through reactive protocol benefits. The algorithm supports network scaling and outperforms the previous heterogeneous algorithm's repeated CH selection process.

Bilal R et al. (2021) [9]presented an EE path planning strategy for WSN addressing energy scarcity, data exchange, and routing protocols (RP) to spread the NLT and enhance connectivity.

This approach was divided into equal areas based on mobile sinks and employs a stable election algorithm (SEP) for message discussion elimination. The SEP was utilized as a clustering method that uses three optimization techniques to assess the performance of optimized mobile sinks' trajectories. They reached a better performance by using the simulation tool of MATLAB simulations.

The authors introduced an approach that outperforms existing schemes and improved up to 66% of network life.Roopali et al. (2022) [10]described various challenges in WSN due to energy-constrained batteries, impacting the efficiency, reliability, and durability of sensor nodes (SNs).

Clustering methods improved EE in WSN, while MIMO antennas were used in 5G transmissions for increased capacity in IoT applications. So, the authors proposed balancing energy utilization (EU) per unit area using IoT devices submerged with MIMO in 5G networks, instead of a single sensor for better load balancing.

The paper presents a 30% improvement in QoE, EU, and NLT using a smart MIMO-based 5 G-composedEE protocol for networks.K. V. Praveen et al. (2021) [4] described the concept of a smart city as encompassing various aspects such as technology, economy, governance, and ensuring unique communication needs.

Wireless technologies were used in Smart City activities, but unlicensed interference and band issues persist, necessitating IoT solutions. The authors developed an ECRR for IoT networks using hybrid optimization techniques. The ECRR technique utilizes DC and meta-heuristic methods and efficiently allocates large IoT devices.

This method was capable of reducing congestion and improving route discovery and is evaluated using the NS2. Jonnalagadda et al. (2023) [11] described IoT infrastructure as necessitating extensive sensory data collection due to limited computational capacity and energy.

That was utilized range for precise value expression in various domain applications. The authors propose the Spanning Tree-Based Flooding Mechanism with Cooperative

Game Theory (STBFM-CGT) as a secure data communication method for IoT-WSN networks, balancing energy consumption and security.

The proposed method reached efficient data transmission in IoT-WSN networks that achieve better results as compared to advanced methods. R. Bharathi et al. (2022) [12] described that WSN Wireless sensor networks face limitations due to limited resources, including were not yet addressed in the IoTs.

The authors proposed a model to enhance rogue node detection in IoT sensor networks before widespread deployment. The implemented three-layer cluster-based WSN routing protocol enhances network energy duration and includes a security mechanism for identifying and blacklisting risky sensor node behavior. The cost-based clustering approach, utilizing IoT in various industries, involves sink nodes selecting clusters and grid heads based on the cost function's value.

The proposed PSO method was utilized to analyze IoT nodes and clustering strategies and highlighted the rapid growth of services, programs, and electrical devices with integrated sensors. Wooseong Kim et al. (2022) [13] described power shortages in IoT WSN, leading to network inefficiency due to limited power source reliance on sensor nodes. The authors developed a novel RP to balance EC among nodes in a WSN, extending network life and route feasibility.The scoring scheme uses node density and energy levels to control the significance of individual nodes in routes.

The proposed model reached superior results compared to other experimental protocols, as demonstrated by simulation results. RoopaliDogra et al. (2022) [14] described WSNs as crucial for IoT, but their linkage presents challenges due to excessive energy usage and short network longevity. This research introduced an improved smart (EERP) to address energy constraints in sensor nodes, enhance data sharing, and extend network lifetime. The Cluster Head (CH) nodes were chosen using an efficient optimization method for sensor node elimination such as sleepy node and decreased energy deployment.

The Sail Fish Optimizer (SFO) was a mathematically researched data transfer method that compares to current methods. The proposed network longevity strategy reached 96% of PDR for 500 nodes. Dr.Srinivasa et al. (2022) [15]described the IoT as an innovative technology that connects physical devices. That enabled data sharing and communication between nodes and third-party services for a common goal. High deployment costs necessitate the use of Internet-connected nodes as gateways for transmitting data to online services. Routing protocols were crucial for network connections and data packet distribution, face significant challenges in IoT use cases due to topology variations caused by node flexibility. The authors developed a model for an enhancement to the formation of cluster protocol with neuro-fuzzy rules. Also, enhances its performance in low-power network scenarios.

The proposed routing algorithms and intelligent approaches. That included fuzzy rules, temporal constraints, and deep learning (DL), which can significantly improve EE in WSN routing processes for safe data packet transfer.

The proposed cluster-dependent routing method was developed, evaluated, and proven to be effective based on various criteria.In Table 1, several existing energy efficiency-based routing protocols IoT in WSN-related methodologies are established with problems, tools, performance metrics, outcomes, and future scope.

Table 1: Study of various existing routing protocols used in WSN-based IoT network

Author's Name	Proposed Method	Problems	Simulation Tools	Metrics	Outcomes	Further Improvements
Zhaoming Ding et al. (2020) [7]	DRA-EE-RS	complexity increases due to network size.	MATLAB, NS3	Packet Reception Ratio (PPR), Energy efficiency (EE)	This method resolves the issue of higher EE of RP.	This method can be enhanced by implementing efficient algorithms, optimizing resource allocation, etc.
Sarvesh Kumar Sharma et al. (2023) [8]	PSO Residual Energy Stable Election Protocol (SEP)	Challenging issues for data transmission and QoS.	Matlab	EE, Alive node, energy consumption, network lifetime	This method enhances network lifetime and supports scaling.	Provides further direction to improve and execute QoS concerning mobile node distribution.
Bilal R. Al-Kaseem et al. (2021) [9]	ACO method	communication and coverage-related issues happened during transmission.	Matlab	Energy consumption Cost Stability Network life	This method improves network lifespan.	This method can be further explored to enhance the performance by reducing energy consumption.
RoopaliDogra et al. (2022) [10]	multiple-input multiple-output (MIMO)	More energy consumption is this method.	NS3	Coverage Delay Network Life Energy consumption	It focuses on a better lifespan of the network and reduces energy consumption.	This method can be the best transmission interface to improve performance.
K. V. Praveen et al. (2021) [4]	ECRR protocol	Inefficient resource allocation	NS2	energy consumption Network lifespan ThroughputE2E delay PDR	This method resolves the issues of resource allocation and routing for better performance.	This method can be further extended by considering another parameter.
Jonnalagadda V.N. RaghavaDeepthi et al. (2023) [11]	STBFM-CGT	More energy consumption, poor transmission, and collision.	*	energy consumption, throughput PDR, Network lifespan	This method reduced the influence of mobility and topology variations.	This method can be implemented with a wired system for example internet.
R. Bharathi et al. (2022) [12]	PSO	More chances of packet loss during transmission.	NS2 C++	Packet loss, Throughput, Network lifetime	This method extends the network life.	This method of clustering algorithms will employ fuzzy logic to determine the network's shortest paths and calculate various parameters such as bandwidth etc.
Wooseong Kim et al. (2022) [13]	a novel routing mechanism	More energy consumption.	Matlab	Average energy Dead node Throughput Energy Consumption Delays	This method solves the issues related to energy consumption.	This method can incorporate game theory and cluster formation-trusted route development.
RoopaliDogra et al. (2022) [14]	An enhanced smart-EE RP (ESEERP)	Complications due to due to excessive energy consumption.	Matlab	Energy utilization PDR Bandwidth Network life	This method powerfully resolve the issues related to sensor nodes.	This method will observe the cluster optimization to improve the performance.
Dr.SrinivasaBabuKasturi et al. (2022) [15]	Cluster Formation Protocol with Neuro Fuzzy Rules	More energy consumption during implementation.	NS2	Network Life Energy consumption	This method provides an efficient IoT-based sensor network routing.	This method can be extended by considering other routing methods.

3. PROBLEM STATEMENT

Generally, IoT combines various technologies to collect, process, and transmit information from ecosystems using embedded sensors, revolutionizing communication and the nextgeneration of technology [20].

The IoT network aims to create a fault-free network of wireless equipment. Routing is crucial as IoT network nodes act as routers and hosts, and data is delivered through gateways.

Several routing [21] techniques have been introduced for SNs and are applicable within the IoTs. IoT networks; main problems [22] are delayedEE and more life routing. Real-world objects can perform similar jobs, so tasks assigned efficiently to these objects are dedicated to minimizing routing, energy, transmission bandwidth, and storage requirements while maintaining quality situations.

IoT is progressively utilized in cities to interchange information as a transmission platform.To create the transmission, perfect methods are employed [23]. The two metrics used forcommunication are intelligence and effectiveness. Also, another problem with accurateinformation is the OR (optimal route).

The OR is formed utilizing the route method to search paths for forwarding information to or from objects in intelligent cities [24]. This method's significant limitation is exploring routes for better QoSand exchanging data [25].

So, developing a skilled strategy by measuring all constrainis a primary limitation. Table 2 describes the existing article analysis with research issuesand gaps for IoT in the WSN network.

Table 2: Existing Analysis

Author Name	Gaps/Issues
Kim et al. 2016 [20]	Current analysis has identified the issue of designing bandwidth allocation approaches using GT (game theory).
Parveen et al. 2021 [4]	Due to energy consumption, congestion, and data loss, the overall the performance was affected, and it needs an optimal route selection method to overcome issues.
Anichur et al.2021 [25]	Noise and data redundancy have affected the network performance, requiring a hybrid routing approach to reduce the problems.

4. MATERIAL AND METHODS

4.1 An energy-efficient congestion-aware resource allocation and routing protocol (ECRR)

The ECRR protocol was developed for IoT networks to utilize hybrid optimization techniques. It also deployed various methods based on clustering, and metaheuristics to powerfully assign large-scale strategies and gateways, in that way reducing congestion. A queue-based swarm optimization procedure was also used for selecting optimal future routes and improving various performance constraints. An ECRR technique and queue-based swarm optimization provide an efficient allocation in large devices and gateways.

ISSN 1462 2815

So, this method describes in detail and their contributions are:

4.1.1 Data Clustering and Meta-Heuristic Method

These methods are used to assign large-scale strategies and gateway. The meta-heuristic algorithm enhances sensor placement and configuration in IoT networks by dynamically adjusting parameters based on real-time data, thereby increasing efficiency and scalability.

The ant clustering algorithm adjusts node clustering based on contextual information like accuracy, reliability, energy, availability, and cost in the clustering process. Figure 1 shows a system model with IoT clustering for efficient operation and large-scale device allocation, optimizing routing processes and reducing congestion through multiple constraints.

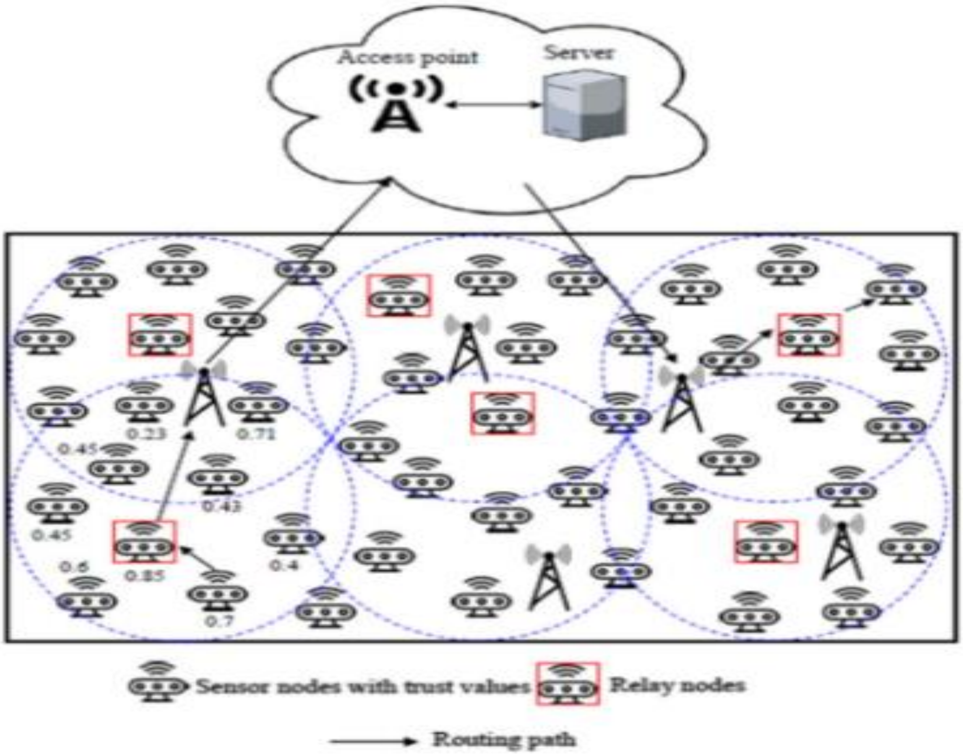

Figure 1: Network Deployed in ECRR method [4]

4.1.2 To develop a cluster by using Grouping Sensors

The search for optimal user assistance sensors involves grouping traffic, road activity, and weather based on context information to create relevant clusters. Clustering involves identifying nearby nodes, building a cluster, and finalizing the cluster head (CH) calculation to form a cohesive network. Neighborhood Discovery involves sensors sending unique IDs, or HELLO messages, to other sensors, developing various neighboring nodes with their corresponding IDs over time.

The HELLO message is utilized by active nodes. The localization process is valid only at specific times, considering neighboring nodes within the frequency transmission range. The total nodes are required to finda degree of neighboring nodes. Cluster construction involves the formation of clusters, incorporating simple synchronization between nodes without time-synchronization.

The initial phase involves loading or unloading an ant agent, identifying the Most Similar Sensor (MSS) for cluster formation, and using unloaded antis to pick up an unvisited node without probability. Ant agents may not consider the impact of dropping a sensor node near the MSS if the random drop is not possible.

The ant's field of view, which increases with cluster size, affects the random dropping of nodes, regardless of memory allocation [4]. Sensors are assigned a cluster number (CN) based on their assigned cluster.

4.1.3 Compute Cluster Head (CH)

The ant clustering method is utilized for the evaluation of CH where nodes merge local maps to create a global map with unique network coordinates. The CH makes the MDS function, reducing computational overhead by selecting a few nodes and adjusting mainly affecting the CH.

It is formed by the center member and is not active but primarily responsible for transmitting and receiving messages. It initiates data aggregation, requests data from other nodes, and tracks the nearest 1 and 2-step neighbors, while CH sends information for tracking.

It uses ant behavior to select sensor nodes from a randomly generated search space Ns, dropping them in MSS using eq. (i) to calculate similarities.

$$f(S_{ni}) = \left(0, \frac{1}{S^2} \sum S_{j \in N(Sj)} \left(1 - \frac{d(S_{ni,,}S_{nj})}{Kp + fSn)}\right)\right) \ldots\ldots\ldots \qquad \text{(i)}$$

$$d(si, sj) = \sqrt{\sqrt{\textstyle\sum_{k=1}^{n} S_{ni}}.\ Ak - Snj.Ak} \ldots\ldots\ldots \qquad \text{(ii)}$$

Eq (ii) is used to compute Euclidean distance and is a factor that determines the dissimilarity scale between two sensors, determining their proximity. The average distance between sensors is calculated using the formula si. Ak, where “si” = kth attribute value and n = all attributes exist in the sensor context data.

$$\mu = \left(\frac{kp}{Kp + f(Sn)}\right)^2 \ \ldots\ldots\ldots\ldots.. \qquad \text{(iii)}$$

$$P_d(S_{ni}) = \left(\frac{f(Sni)}{kd + f(Sni)}\right)^2 \ \ldots\ldots\ldots\ldots \qquad \text{(iv)}$$

The overall number of nodes is represented by Sn. It collects and drops prospects are calculated using eqs. (iii) and (iv) after searching for similarities. The ant response threshold parameters, k_p, and k_d, impact picking up and dropping patterns, with higher values increasing pick-up and decreasing dropping probability. The selection of a new sensor is crucial for ant movement, as it determines the direction of their movement towards the last dropped similar nodes. Algorithm 1 for CH calculation is described as;

Algorithm 1: For CH Calculation

- Randomly scatter Sn in Ns.
- if (ant_agant unloaded)
- Sn is unattained, PuSn and Sni from the unattended list
- else

ISSN 1462 2815

- if(ant_agant=loaded)
- Sn is nominated by the ant_agent
- drop SN near to MSSin the area
- Modificationin SN, to the MSS Sni *CN← MSS*CN
- else
- if (ant_agent loaded)
- inefficient to find similar nodesand dropped in the space
- Evaluatenew CN to Sn
- SNCN←CN_new
- End
- for (each Ag)
- if (Ag = selected randomly)
- else
- drop Sn only
- end
- if $(\alpha > \ \delta)$ updates the positions
- if (f(i)>0)
- if (S2, s2max)
- End
- If (num<threshold)
- New node join check for MESH
- End
- If (context property of nodes)
- Find the new node based on MESH
- Update the cluster of sensor
- If (left the node)
- Elimination of nodes from the cluster
- modified CH
- End
- Modifiednum> threshold)
- num = 0
- End
- Return cluster_formation

ISSN 1462 2815

4.1.4 Queue-Based Swarm Optimization Algorithm for Better Route

Seeley's 1995 behavioral model suggests a self-organization model for honey bee colonies, where foraging bees visit flower patches and return with nectar and profitability ratings. The nectar collected is used to assess the quality measured using the profitability rating function. The waggle dance is a self-organized model used by individual foragers to learn about a forested patch, locate a hive, and provide feedback on food sources' quality.

$$t_i(j+1) - tij \geq tij \;\; \forall(Oij, Oi(j+1)) \in Ai \ldots \qquad \text{(v)}$$

Job Shop Scheduling optimizes objective functions by sequentially allocating computing resources. J = finite set jobs, managed in a finite set M = machines in a pre-determined order, without interruption or pre-emption.

$$t_{ij} - tkl \;\; \geq tkl - tij \geq tij \;\; \forall(Oij, Okl) \in E \ldots \qquad \text{(vi)}$$

The problem of job shop scheduling is modeled as a system where a single machine can execute a job at a time, with the longest time interval being Smat time tij. The makespan factor is utilized in research to address jobshop scheduling issues, addressing the fundamental computational problem inherent in optimal schedule planning.

The makespan simplifies and minimizes the problem of job shop scheduling by using a disjunctive graph with nodes representing the job. The graph uses source and sink nodes to represent initial and final operations, with positive weights indicating processing time, aiding in understanding job shop issues.

A forager follows a chosen dance path, which guides its direction for flower patches, ensuring the optimum path is chosen for optimal performance. The forager's path from the hive to the nectar involves several landmarks and profitability of the objective function;

$$Pri = \frac{1}{cnmax} \ldots\ldots\ldots\ldots\ldots\ldots \qquad \text{(vii)}$$

ineq (vii), makespan = Ci max, while the average chance ratio of bee colonies is calculated using the following formula in (viii):

$$P\_colony = \frac{1}{n}\sum_{j=1}^{n} \frac{1}{cnmax} \ldots\ldots\ldots \qquad \text{(viii)}$$

where, n = total waggle dances, t = period. di is given by

$$di = \frac{Pri}{cnmax} \ldots\ldots\ldots\ldots \qquad \text{(ix)}$$

Algorithm2 of query-based is described as:

Algorithm 2: Query-Based Algorithm

- Setoij, Mx, Tij
- For (tij =1)
- Oil is processed by M1
- count = sm1
- Calculate tij and Tij

- else
- Rise task
- Determine the profitability ratio for a forager
- if(Pr1>Pr2)
- Higher priority job = j1
- else
- higher priority job = j2
- calculate the probability rating of bee colonies and the distance
- (if (d'>low)
- The optimal route
- else
- repeat the step forthe shortest path distance identified
- end
- Return routing process

4.2 Enhanced Swarm Distributed Energy-Efficient Clustering Scheme (ES-DEEC)

The research framework will show the flow of the implemented approach. The framework for initializing network development defines the base station, search source, and destination node. It has several phases that sense and process the data packets and transmit them to the destination node.

It will help the WSN-based IoT network transmission and give necessary details of the real world at the top center for future storage of sensitive information. All the WSN-based IoT network framework steps define several phases of the whole network.

It comprises deploying nodes responsible for network placement in a particular area. When the network is deployed, the other steps include initial parameters, coverage setting, distance, energy, initial time, transmission range, etc., of the network.

The WSN-based IoT network node uses an optimized route selection technique to transmit data packets efficiently, selecting the source and destination nodes.This method will help to select the reliable route for data transmission and overcome the existing problems—WSN-based IoT network performance metrics like energy, packet loss, etc.

These are obtained at the end of all transmission time to evaluate the research flow capability. An enhanced network performance defines the quality of service and improved or better communication between the network.

Figure 2 shows the research methodology flow chart in the WSN-based IoT network. The proposed flowchart will have several steps, such as initial network development, coverage set design, routing process for data transmission, and enhanced method implemented to improve the performance parameters and comparison analysis.

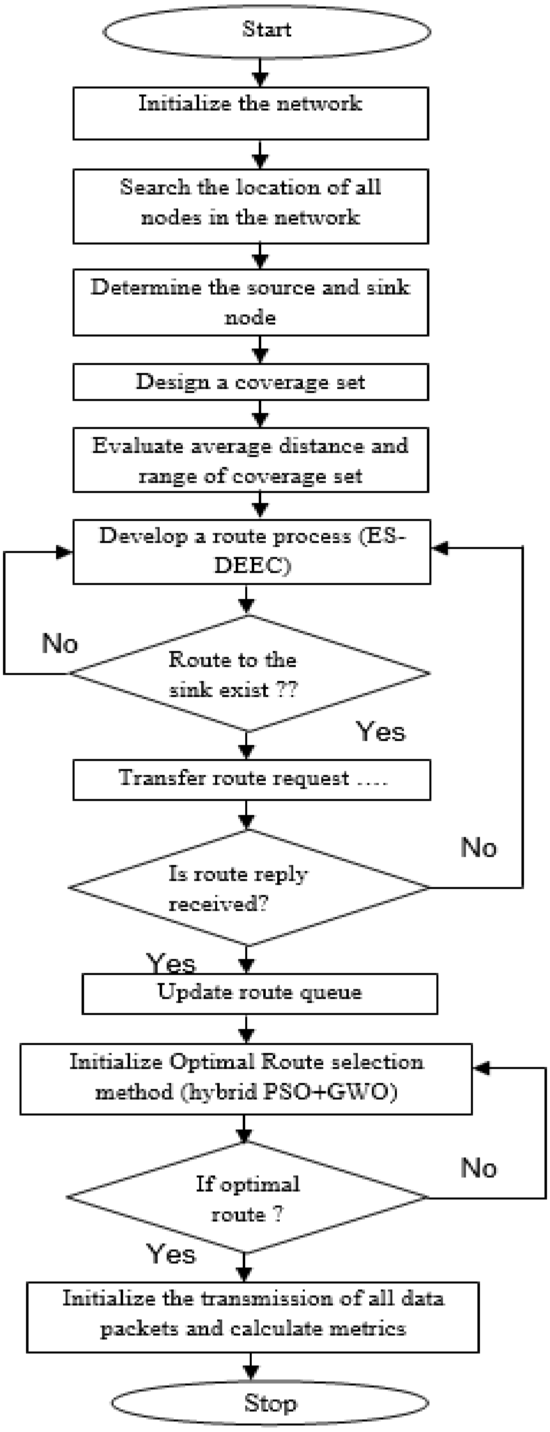

Figure 2: Proposed Flow Chart

4.2.1 ES-DEEC protocol

ES-DEEC is an EE protocol for heterogeneous WSNs, dividing as clusters with sensor nodes and CH. The Cluster Head (CH) calculates the probability function based on residual and average network energy, with higher computation values indicating a higher CH selection likelihood.WSN uses a CH selection algorithm to select CHs, collect data, and send it to BS, influenced by RE and network average.

4.2.2 Heterogeneous Network Model

The experiment uses a m*m square region network model with n stationary nodes, with the BS at the center and CHs for aggregated data transmission. SNs are classified into advanced and normal types, with initial energy denoted by Eo.Total advanced nodes have mN energy, while total normal nodes have (1-m)N energy. The following equation (x) is used to find the initial energy of a two-level heterogeneous model.

$$\mathrm{E_{total}} = \mathrm{N1'(1 - m')E0 + N1'\_m'E0\,(1 + a) = N1'\_E0\,(1 + am')} \ldots\ldots\ \ldots \quad \text{(x)}$$

4.2.3 Method for CH Selection

CH selection involves a probability function for each node with varying energy values, calculated as eq (xi) after ni rounds.The probability of a node being a CH after ni rounds can be designed as in eq (xi).

$$\mathrm{Pi} = \frac{1}{ni} \ldots\ldots\ldots\ldots \quad \text{(xi)}$$

In eq (xi), Pi = energy level of nodes in each round, and $\mathrm{P\_out}$ = energy level of nodes with different levels. The average energy of a network can be calculated with the help of eq (xii).

$$\bar{\mathrm{E}}(\mathrm{r}) = \frac{1}{N}\sum_{i=1}^{N} Ei(r) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad \text{(xii)}$$

In eq (xiii), Pi = reference energy, probability of ith node.

$$\mathrm{Pi} = \mathrm{P_{out}}\left[1 - \frac{\bar{\mathrm{E}}(\mathrm{r}) - \mathrm{Ei\,(r)}}{\bar{\mathrm{E}}(\mathrm{r})}\right] = \mathrm{P\_out}\ \frac{\mathrm{Ei\,(r)}}{\bar{\mathrm{E}}(\mathrm{r})} \ldots \quad \text{(xiii)}$$

The average number of clusters/epoch is recognized in eq (xiv).

$$\sum_{i=1}^{N} \mathrm{Pi} = \sum_{i=1}^{N} \mathrm{P_{out}} \frac{\mathrm{Ei\,(r)}}{\bar{\mathrm{E}}(\mathrm{r})} = \mathrm{P_{out}} \sum_{i=1}^{N} \frac{\mathrm{Ei\,(r)}}{\bar{\mathrm{E}}(\mathrm{r})} \mathrm{P_{out}} N \ldots\ldots \quad \text{(xiv)}$$

In eq (xv), T(si) = threshold probability It defines whether Si can become a CH.

$$T_{si} = \left\{ \frac{pi}{1 - pi(rmod\frac{1}{pi}} if Si \in G \right\} \ldots\ldots\ldots\ldots \quad \text{(xv)}$$

In each round, if Si is eligible for CH, a random number between 0 and 1 is selected based on a threshold value, and if less, the node acts as CH. The inverse of Pi is chosen in eq (xvi).

$$\mathrm{ni} = \frac{1}{pi} = \frac{\mathrm{Ei\,(r)}}{\mathrm{P\_out}\bar{\mathrm{E}}(\mathrm{r})} = n\ _{opt} \frac{\mathrm{Ei\,(r)}}{\bar{\mathrm{E}}(\mathrm{r})} \ldots\ldots \quad \text{(xvi)}$$

In eq(xvii), suggests that high residual energy (RE) nodes have a higher chance of being elected as cluster heads. Energy dissipation can be reducedand calculations the number of nodes.

$$\mathrm{P}_{adv} = \frac{P_{out}}{1+am}, \mathrm{P}_{nrm} = \frac{P_{out}(1+\alpha)}{1+\alpha m} \ldots\ldots\ldots \quad \text{(xvii)}$$

In eq(xviii), the Psi is described as the weighted probability and Pi can be calculated for multi-level heterogeneous networks in eq (xix).

$$Psi = \frac{Pout\ N(1+\alpha 1)}{N + \sum_{i+1}^{N} \alpha i} \ldots\ldots\ldots\ldots\ldots\ldots \quad \text{(xviii)}$$

$$Pi = \frac{Pout\ N(1+\alpha)Ei(r)}{N + \sum_{i+1}^{N} \alpha i)\bar{\mathrm{E}}(\mathrm{r})} \ldots\ldots\ldots\ldots\ldots\ldots \quad \text{(xix)}$$

4.2.4 Energy Consumption (EC)

ES-DEEC calculates average probability using average and total energy, aiming to prolong network lifetime by efficiently distributing energy consumption among nodes, providing accurate network performance estimations in eq (xx)

$$\bar{\mathrm{E}}(\mathrm{r}) = \frac{1}{n} E_{total\left(1-\frac{r}{R}\right)} \ldots\ldots\ldots\ldots \quad \text{(xx)}$$

In eq(xxi), R = network lifetime.

$$R = \frac{E_{Total}}{E\_round} \ldots\ldots\ldots\ldots\ldots\ldots \quad \text{(xxi)}$$

In eq (xxii), the energy expansion is calculated which is defined in terms of the radio broadcast of l-bit message and distance (d).

$$E_{Tx}(1, d) = \begin{Bmatrix} IE_{elec} + 1 \in fsd^2 d < d0 \\ IE_{elec} + 1 \in mpd^4 \quad {}_{d>d0} \end{Bmatrix} \ldots\ldots\ldots\ldots \quad \text{(xxii)}$$

In eq(xxiii), it calculates energy dissipation in a network by dividing it by the number of bits sent by each node, determining network efficiency and performance.

$$E_{round} = L\ (2NE_{elec} + NE_{DA} + k\varepsilon mpd^4_{ChtoBS+N\epsilon fsd^2_{NtoCH}} \ldots\ldots\ldots\ldots\ldots\ldots \quad \text{(xxiii)}$$

In eq(xxiv), the formula calculates the average distance between clusters (k), data aggregation cost (EDA), and node and cluster (dCH to BS and dN to CH).

$$d_{toCH} = \frac{M}{\sqrt{2\pi k}},\ d_{toBS} = 0.765\frac{M}{\sqrt{2\pi k}} \ldots\ldots \quad \text{(xxiv)}$$

4.2.5 Hybridization Optimization (PSO-GWO) Method for Best Round Searching

Optimization problems In engineering domains often require complex solutions. Numerical approaches, such as meta-heuristic algorithms, can help, but global optimization isn't guaranteed. Hybridizing GWO-PSO algorithms can merge their strengths for better results. These methods are discussed as below sections.

The PSO belongs to the meta-heuristic optimization family inspired by bird flocking or fish schooling. It generates an initial population randomly within a search domain, keeping the best location and position information in memory. In each iteration, modify the location of the particle. The PSO is a swarm-related meta-heuristic optimization technique that uses a population-based examination strategy to find the optimal population for a problem. Particles are generated in a multi-dimensional exploration field, using their own and neighboring experiences to adjust their position. The PSO is easy to perform and requires no parameter adjustments, with changes in velocity items set according to specific rules. Its strengths lie in its simplicity and effectiveness.

$$\bar{x}_{n+1} = \bar{x}_{n+1} + \bar{V}_{n+1} \ldots\ldots\ldots\ldots\ldots \quad \text{(xviii)}$$

$$\bar{V}_{n+1} = w\bar{V}_n + c1r1\left(\bar{p}_{n-\bar{x}_n}\right) + c2r2(p^g{}_n - \bar{x}_n\ ) \ldots. \quad \text{(xix)}$$

The text describes a swarm model with parameters i, n, r1, r2, a, b, c1, c2, x, v, p i, and pg, where i represents the particle, n represents the iteration step, r1 and r2 represent random numbers, a is the inertia weight parameter, and pgdefines position information. The PSO algorithm replaces a particle's new position and velocity with a random one to avoid local minimums [17].

ISSN 1462 2815

The GWO technique, developed by Mirjalili et al., uses grey wolves as solutions to optimization problems, with alpha wolves being the best. The algorithm updates solution positions iteratively, following the social grading and hunting behavior of grey wolves (GWs) [18]. The algorithm assigns alpha solutions as the best, beta solutions as the second-best, and delta solutions as the worst, allowing efficient examination and mistreatment of the search space [17]. The omegas (x) are the least-priority wolves, following the leading GWs. The GWO technique is explained mathematically. The GWO algorithm identifies four GWs: alpha, beta, delta, and omega. Alpha is the best solution, followed by beta delta, and omega. GWs hunt by tracking, chasing, approaching, pursuing, encircling, harassing, and attacking prey, with mathematical models for encircling the prey.

$$C * Xp(t) - X\_1'(t) \;\ldots\ldots\ldots\ldots\ldots \qquad \text{(xx)}$$

$$X\_1'(t-1) = X\_1'(t+1) - A\_1 * D\_1 \ldots\ldots\ldots \qquad \text{(xxi)}$$

The equation calculates vectors A and C, representing the prey position and the location of grey wolves.

$$A = \mathrm{a} * (2 * \mathrm{r1} - 1) \;\ldots\ldots\ldots\ldots\ldots\ldots \qquad \text{(xxii)}$$

$$\mathrm{C} = 2 * r_2 \ldots\ldots\ldots\ldots\ldots\ldots\ldots \qquad \text{(xxiii)}$$

The GWO algorithm uses grey wolves, led by alpha wolves, to detect prey locations, with beta and delta wolves occasionally aiding. Iterations decrease linearly from 2 to 0, with alpha wolf as the best solution.

causing other wolves to follow.

$$\mathrm{D'}_n = \mathrm{C\_1'} \times \mathrm{Xn} - \mathrm{X(t)}|, \mathrm{D}n = |\mathrm{C\_2} \times \mathrm{X}n - \mathrm{X(t)}|, \mathrm{D}n = |\mathrm{C\_3'} \times \mathrm{X}n - \mathrm{X(t)}| \ldots \qquad \text{(xxiv)}$$

$$\mathrm{X1} = |\mathrm{Xa} - \mathrm{a1Da}|, \mathrm{X2} = \mathrm{X\beta} - \mathrm{a2Da2}|, \mathrm{X3} = \mathrm{X\gamma} - \mathrm{a3Da3}| \ldots\ldots \text{(xxv)}$$

$$X_p(x-1) = \frac{x1+x2+x3}{3} \ldots\ldots\ldots\ldots\ldots\ldots \qquad \text{(xxvi)}$$

The location of new prey is determined by dividing the mean of the three best wolves by t+1, with grey wolves attacking prey and existing hunts abandoned if |A| is greater than or equal to 1.If prey is close enough, grey wolves attack, preventing local minimums. Algorithm 3 described the main flow of the optimal route search.

Algorithm 3: Hybrid PSO-GWO Method: Optimal Route

Input_data:- M_x, N_{pop}, P_{rob}, P_{i1}, W_{i1}

// M_x: the no. of maximum iterations set by the user

// N_{pop}: the no. of population sizes set by the user

// P_{rob}: Probability rate by the user

Output_data:- Routing Procedure with DEEC method

Initialize the metrics such as M_x, N_{pop}, P_{rob}, and Particles

For (N_{pop} =1)

P_{i1} is processed by M_x

Count_data = W_{i1}

Evaluate the N_{pop} and P_{rob}

Else

i++

evaluate the $P_{rob}$for particles and wolves

if ($Prob_{data1}$ > $Prob_{data2}$)

maxima_priority = i1;

else

maxima_priority = i2;

evaluate $P_{rob}$of Wolves and distance (dist)

if dist is less

the optimal solution with the finest route is recognized.

Else

Repeat the step-up to the minimum distances recognized

End

Return routing procedure (DEEC) method

5. EXPERIMENTAL RESULT ANALYSIS

The research work used the MATLAB simulation tool with the different metrics, defined in Table 3, to perform the experimental simulations for calculating the implemented ES-DEEC routing protocol. The proposed protocol performances are compared with the existing protocols like ECRR. The proposed model has evaluated the different metrics such as E2D (end-to-end delay), PDR, EC, Throughput (Th), etc.

Table 3: Experiment Simulation Metrics

Metrics	Values
Network Size	1000*1000
Network topology	Uniform
Initial time	2-5 sec
Location of devices /nodes	Randomly deploy
Number of nodes/devices	0-100
Speed	10 meters per second
Mobility model	Randomly
Parameters	E2D, PDR, Network Throughput, etc.
Proposed protocol	ES-DEEC
Comparison protocols	ECRR

The section shows the different metrics, such as PDR, EC, NLT, and network Th are analyzing the different numbers of nodes. Below figure 3 depicts the E2D analysis w.r.t the number of SNs. The result analysis is compared with the previous methods such as ECRR, AODV, etc. When the E2D minimum then the information will be transmitted speedily. The figure plotting shows the E2D of the implemented ES-DEEC protocol is very low in the form of 8 sec and 11 sec compared to the existing ECRR routing method. Figure 4 shows the variation of EC with different no. of SNs. The EC is minimum in researched ES-DEEC protocol as compared with the existing method

ISSN 1462 2815

ECRR. The graphical representation of the EC of implemented ES-DEEC is much less in the form of 28 and 30 joules compared to the existing ECRR protocol.

Figure 3: E2D to Number of SNs

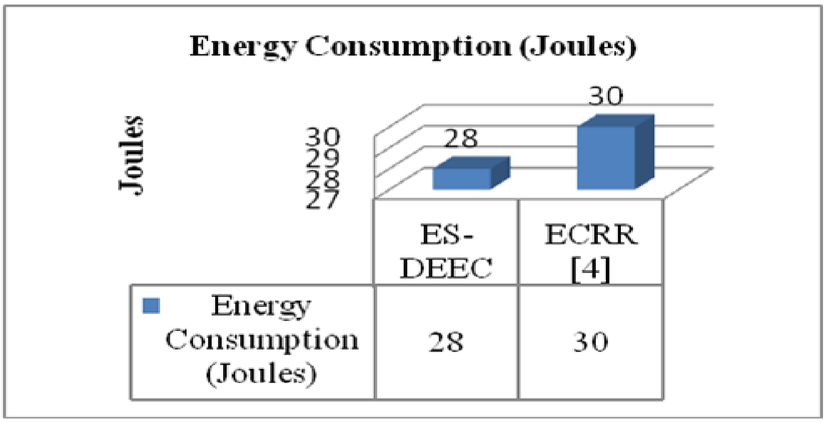

Figure 4: Energy Consumption to Number of Nodes

Below figure 5 represents the packet delivery rate (PDR) with different no. of SNs. From the analysis of the implemented ES-DEEC protocol the PDR is the maximum that helps for the quick delivery of the data packets. The graphical representation clearly defines the PDR of the implemented ES-DEEC protocol as a maximum of 80 and 62 percent compared with the existing methods.

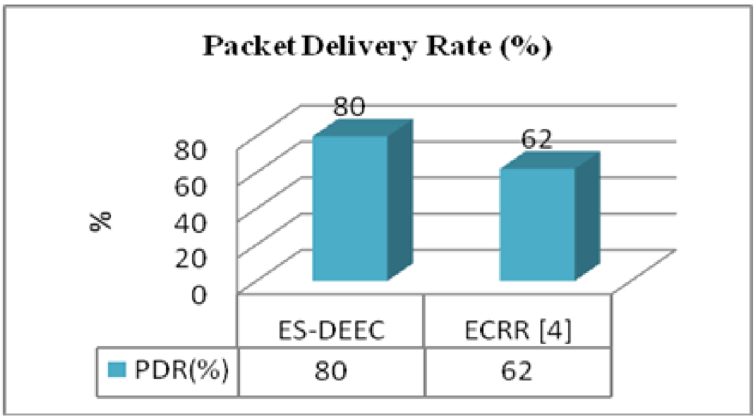

Figure 5: Packet Delivery Rate to No. of Sns

Figure 6 gives the study of network Th with different numbers of SNs. The experimentaloutcomedepicts that the network Th is the maximum for the introducedES-DEEC protocol as compared to the existing ECRRprotocol. The graphical plot clearly shows the network TH of introducedES-DEEC is maximum in the form of 89 and 65 percentcompared to existing ECRR protocols.

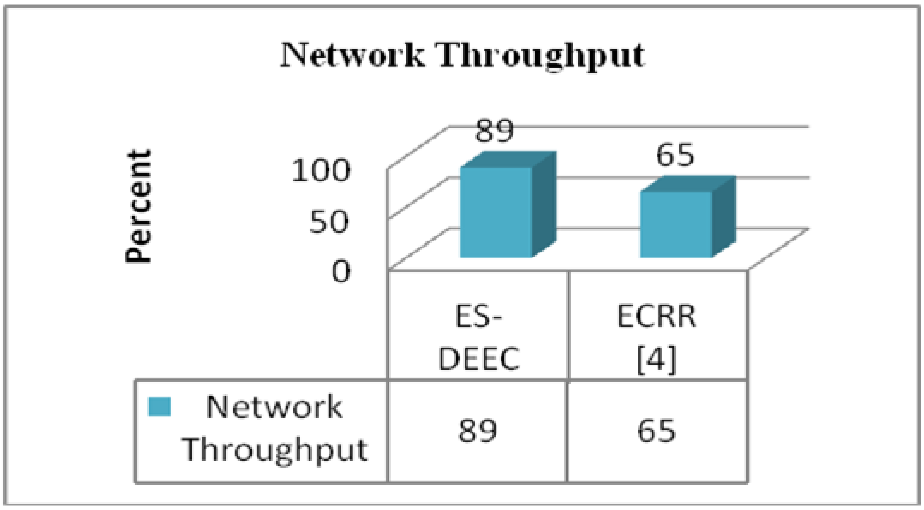

Figure 6: Network Throughput to Number of SNs

Figure 7 depicts the study of NLT of the network. The implemented ES-DEEC protocol has having highest NLT which will reduce the commonbattery replacement. The graphical representation of the NLT of implemented ES-DEEC is very high in the form of 90 and 87 percent compared to the existing ECRR method.

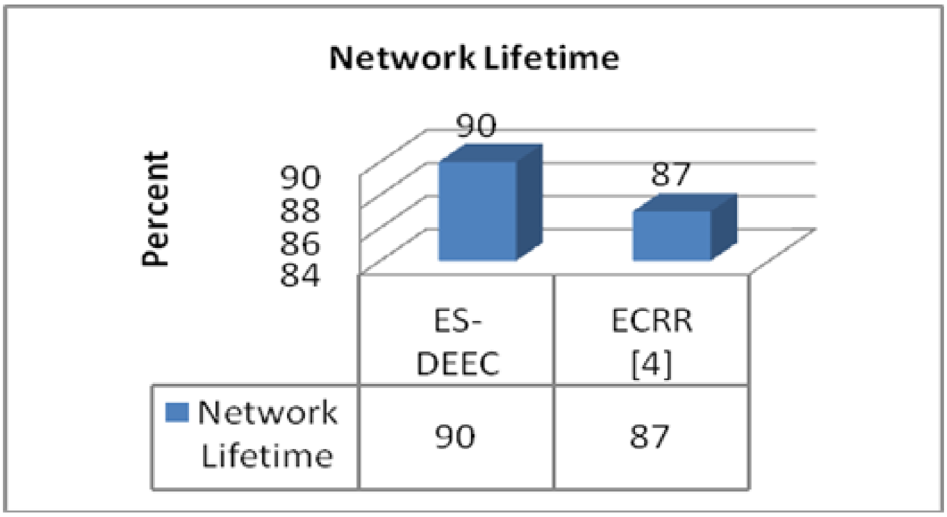

Figure 7: Network Lifetime to Number of SNs

6. CONCLUSION

The research work concluded main motive of the research work is to explore the effectiveness and intelligent routing method to enhance the transmission of IoT in smart cities. The routing algorithm optimizes data packet communication by considering factors like network traffic, link quality, and shortest path. It continuously analyzes and updates routing tables, improving network performance.The experimental result analysis is carried out in MATLAB tool.The experiment result analysis is performed and evaluates the network performance metrics, such as network TH, NLT, PDR, Delay, etc. So, the researched routing method has better performance as compared with the existing ECRR method.

Acknowledgment

None

Conflicts of Interest

The author has no conflicts of interest to declare.

Data Availability

Not Applicable.

Author Contributions

Anuj Kumar: Analysis of the detailed concept, network deployment, problem statement, and draft manuscript preparation, writing draft, and result analysis. **Dr. Krishna Kant Agrawal:** Supervision, writing, editing and reviewing.

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Appendix

Appendix I	
Abbrevations	**Descriptions**
ESDEEC	Enhanced Swarm Distributed Energy-Efficient Clustering Scheme
RA	Resource Allocation
NLT	Network Lifetime
NT	Network Throughput
EC	Energy Consumption
PDR	Packet Delivery Rate
GWO	Grey Wolf Optimization
Iot	Internet Of Things
PSO	Particle Swarm Optimization
WSN	Wireless Sensor Networks

Qos	Quality-Of-Service`
EE	Energy-Efficient
ECRR	Energy-Efficient Congestion-Aware Resource Allocation And Routing Protocol
LPL	Low-Power Lossy
FT	Fault Tolerance
EELSR	Energy-Efficient Link Stable Routing
AODV	Adhoc On-Demand Distance Vector
REL	Routing Protocol Based On Energy And Link Quality
EERP	Energy Efficient Routing Protocol
RS	Relay Selection
SDWSN	Software-Defined Wsns
SEP	Stable Election Protocol
RE	Residual Energy
SEA	Stable Election Algorithm
Rps	Routing Protocols
Sns	Sensor Nodes
EU	Energy Utilization
MIMO	Multiple-Input Multiple-Output
STBFM-CGT	Spanning Tree-Based Flooding Mechanism With Cooperative Game Theory
CH	Cluster Head
SFO	Sail Fish Optimizer
DL	Deep Learning
ACO	Ant Colony Optimization
OR	Optimal Route
MSS	Most Similar Sensor
E2D	End-To-End Delay