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RESEARCH ARTICLE

Energy-Efficient Clustering and Routing in IoT-Assisted WSN Using Cauchy Mechanism Pufferfish Optimization Algorithm

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Abstract – In Internet of Things (IoT), Wireless Sensor Networks (WSNs) play crucial role on data sensing and collection for the Base Station (BS) communication. In WSN-IoT, the primary challenge is the efficient management of limited energy resources during communication with IoT-integrated devices. Clustering algorithms consume abundant energy to maintain the network node processing over extended periods. Conventional algorithms typically rely on random probability in Cluster Head (CH) selection. Therefore, improving the network lifetime requires the development of enhanced CH selection algorithms. This study proposes an Energy-based Cauchy Mechanism – Pufferfish Optimization Algorithm (ECM-POA) for ideal CH selection and route path selection. Cauchy mechanism is incorporated in traditional POA for enhanced global search capabilities for effective CH and route path selection. Fitness functions like residual energy, intra to inter cluster distance, distribution density parameter and Intra-cluster Communication Cost (ICC) are taken into consideration for a selection of optimal CHs. The developed ECM-POA obtains the highest network throughput of 99.34% for 100 nodes, 98.87% for 200 nodes, 98.26% for 300 nodes, 97.71% for 400 nodes and 97.15% for 500 nodes. These results prove superiority of the proposed model against existing models. The ECM-POA algorithm offers energy efficacy with enhanced network lifetime in WSN-IoT through optimized CH and route path selection.

Index Terms – Base Station, Cluster Head, Internet of Things, Pufferfish Optimization Algorithm, Route Path selection, Wireless Sensor Networks.

1. INTRODUCTION

Recently, Wireless Sensor Network (WSN) technology has been growing rapidly and is expected to surpass personal computers in the terms of relevance and pervasiveness in daily applications [1]. This growth is driven by the increasing availability of inexpensive Sensor Nodes (SNs) which are capable of sensing, tracking and collecting information from the desired areas in real-time [2]. The primary advantage of integrating WSNs is their distributed intelligence and low operational costs [3]. Their wide applicability in real-time monitoring is made possible by distributed intelligence abilities of WSN [4]. This capability contributes to a broad range of innovative applications which includes critical services such as military and emergency response services, which rely on real-time information for seamless planning and coordination [5-7]. The Internet of Things (IoT) integrate various techniques, including cloud techniques, big data and WSNs [8]. IoT facilitates the seamless interconnection of numerous devices, thereby enabling WSNs for an effective communication. [9].

Numerous IoT applications rely heavily on WSNs to accomplish essential tasks of IoT such as data collection and transmission to the Base Station (BS) [10-12]. A major challenge in developing IoT lies in ensuring the reliable data transmission across wide range of WSNs. This highlights the requirement of identifying the innovation approaches that maximize network lifetime [13, 14]. Several researchers have deployed cluster-depended hierarchical algorithms to address the limitations of the compromised network lifetime and scalability [15, 16]. The management of Cluster Head (CH) nodes remains as a primary focus of clustering and routing systems [17]. The CH receives the data from cluster nodes, oversees the information integration from localized cluster members and transmits to BS [18]. This imposes an additional strain on the CH, resulting in the higher energy consumption when compared to normal nodes. Furthermore, CHs also act

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as Relay Nodes (RNs) to transmit packets that are received from distant CHs to the BS, which leads to accelerated energy depletion [19, 20]. Though meta-heuristic algorithms develop an objective function by considering certain primary factors for optimum CH selection and the goal remains to minimize energy consumption.

The Energy-based Cauchy Mechanism – Pufferfish Optimization Algorithm (ECM-POA) is developed to overcome the limitations of traditional clustering and routing algorithms in WSN-assisted IoT networks. However, traditional algorithms suffered from poor global search ability and imbalanced energy usage because of the random CH selection. By integrating Cauchy mutation mechanism to Pufferfish Optimization Algorithm, it improves the global exploration and prevents premature convergence, thereby ensuring robust optimization performance.

The algorithm adopts multi-objective fitness function integrating residual energy, intra-to-inter cluster distance, node distribution density and Intra-cluster Communication Cost (ICC), that causes energy-efficient CH selection and optimal routing. This biologically inspired predator prey dynamics reinforce the exploration and exploitation balance in the optimization process. This hybrid strategy ensures ECM-POA prolongs the network lifetime efficiently and maintains high residual energy level as well as minimize transmission delays.

In the extensive research on clustering and routing in WSN-IoT, existing algorithms suffer from an unbalanced energy usage, premature convergence and limited scalability in large dynamic networks. Traditional protocols rely on random CH selection, that accelerates energy depletion of certain nodes and shortens network lifetime. To address these limitations, this manuscript introduced ECM-POA that combined Cauchy mutation strategy into POA to improve the global search, avoid local optima and obtain balanced energy distribution. By adapting multi-objective fitness function which considers residual energy, intra-to inter-cluster distance, node distribution density and intra-cluster communication cost, the proposed model ensures robust CH selection and efficient routing for WSN-IoT networks.

1.1. Problem Statement

In WSN–IoT, effective utilization of limited energy resources remains as a challenge, particularly in clustering and routing processes. Traditional clustering approaches generally rely on random selection of CHs, causing unbalanced energy consumption, rapid depletion of CH nodes, and reduced network lifetime. Additionally, existing algorithms depend upon significant parameters such as node distribution density, intra-to-inter cluster distances, and communication costs, which lead to suboptimal performance in large-scale dynamic WSN–IoT environments.

1.2. Objective

Primary objective of this manuscript is to develop the Energy-based Cauchy Mechanism – Pufferfish Optimization Algorithm (ECM-POA) to obtain efficient CH and route path selection on WSN-assisted IoT networks. This algorithm aims to improve the network lifetime and throughput by incorporating a Cauchy mutation strategy into the traditional POA, thereby enhancing the global search efficacy. The developed model uses multiple fitness parameters, like residual energy, intra-to-inter cluster distance, distribution density, and intra-cluster communication cost, to develop energy-efficient clusters and choose optimal routing paths that minimize energy consumption and communication delay across the network.

1.3. Contributions

The key contributions of this study are described as:

- ECM-POA is developed to improve selection of CHs and routing paths in WSN-IoT networks, thereby improving energy efficiency and maximizing network lifetime.
- Incorporating a Cauchy mutation strategy into the traditional POA, the global search ability of the algorithm is improved, thereby helping to avoid premature convergence and enhance optimization results.
- The model uses fitness functions like residual energy, intra-to-inter cluster distance, distribution density, and intra-cluster communication cost to guide CH selection and routing path decisions.

This manuscript is further formatted as follows: Section 2 analyses existing algorithms, taking into account their advantages and limitations. Section 3 presents the model's approach to cluster-based routing. Section 4 provides the outcomes of the developed algorithm in comparison with the existing models, while Section 5 discusses the experimental outcomes, and at last, Section 6 concludes this research.

2. LITERATURE REVIEW

In recent years, numerous research studies have developed for cluster and routing of WSN-IoTs using various approaches. This section discusses the most notable approaches along with their advantages and limitations.

Rekha and Garg [21] introduced K-means and Lion Optimization Algorithm for Energy-efficiency Clustering and Routing (K-LionER) on WSN-IoT. Introduced method focused on increasing the network lifetime and enhancing the energy efficacy. Clusters in WSN were developed by K-means, and every CH was selected by Ant Lion Optimization (ALO). CHs collected information from its cluster members and broadcast aggregated data to Base Station (BS). The introduced K-LionER selected a CH that depended on the routing fitness of Residual Energy (RE), distance among CHs and BS, and Intra-cluster Communication Cost (ICC).

Roberts and Ramasamy [22] introduced the Enhanced High-Performance Cluster-Enabled Secured Routing Protocol (EHPC - SRP), which was reliable and an energy-efficient approach. Primary features of the model were packet mitigation, energy efficiency, encrypted data transfer, congestion management, and attacker node surveillance for enhancing data management quality. The CH discovery was based on residual energy, though the data broadcasting distance was also considered in WSN-IoT.

Verma and Jha [23] suggested the Mutation Grounded Multi-Layer Perceptron (MUMLP), where energy and secured optimum routing were computed offer a secured information broadcasting while minimizing the broadcast time. For Data Aggregation (DA), through developing a Boltzmann Selection Probability–centric Gravitational Search Algorithm (BSP-GSA), optimum CHs were chosen. Then, non-cluster members were combined with adjacent CH to develop cluster. Information collected by CHs from non-cluster members was secured by using Improved Elliptical Curve Cryptography (IECC) mechanism.

Tan and Nguyen [24] presented an Energy-Efficiency Routing Algorithm using Hybrid Algorithms (EERHA) on WSN-IoT. Initially, the method was commenced with the strategy of deploying sensor nodes over an observation area, followed through an optimum clustering procedure. This process integrated k-Medoids technique to Elbow algorithm, ensemble obtained from Machine Learning (ML), to define more efficient clustering. The protocol employed a CH to every cluster. Selection criteria of CH nodes depended on the Entropy Weight Coefficient (EWC), that compressed numerous essential parameters such as node distribution density, residual energy, and intra-to-inter cluster distances. In final stage, protocol employed Bellman-Ford approach, which reduced communication costs, specifically across extended links.

Vazhuthi et al. [25] implemented energy-efficient inter-cluster routing and fault management was developed to increase the Quality of Services (QoS) of IoT-WSN. Initially, a Hybrid Adaptive Neuro-Fuzzy Inference System–Reptile Optimization Algorithm (ANFIS-ROA) was developed to identify the optimal routes from a cluster to a sink. Then, a tuned supervision-enabled fault diagnosis policy was applied to diagnose various faults such as sensing faults, communication faults, and residual energy faults in IoT-WSN.

Priyanka et al. [26] presented region-based clustering and cluster-based selection technique to enhance the energy efficacy on IoT networks on agricultural environments. Their model employed Shortest Routing and Less Cost (SRLC) approach along with the Region Clustering and Cluster Head Selection (RCHS) method to improve the energy efficacy. Bhukya Suresh and G. Shyama Chandra Prasad [27] used an improved version of Low-Energy Adaptive Clustering Hierarchy (LEACH) protocol which aimed at stable and energy-efficient CH selection. Their model stabilized the random number generation through incorporating a rank-based CH selection process considering node coverage, energy consumption rate, and base station distance parameters.

Mehra et al. [28] introduced the Load-Balanced Efficient Clustering and Routing (LBECR) technique which was designed for sustainable IoT deployments in smart cities. In their work, the resource-constrained nodes in ad hoc IoT networks dealt with a variety of input variables in the fuzzy system, which caused an increase in the number of rules and consequently resulted in higher energy dissipation. Nevine Makram Labib et al. [29] implemented the Enhanced Threshold Sensitive Distributed Energy-Efficient Clustering (ETSDEEC) routing algorithm to WSN-based IoT. Their protocol utilized the hard and soft threshold to determine when nodes were allowed to transmit the sensed information.

Javadpour et al. [30] developed a novel algorithm by integrating fuzzy clustering to connect the complex sensors to the network with a particle optimization to approximate the initial cluster head scores within the WSN IoT context. Shashank Singh and Veena Anand et al. [31] applied a hybrid optimization algorithm by integrating fuzzy c-means and Grey Wolf Optimization (GWO) for clustering purposes.

Pandey et al. [32] proposed an energy-efficient method for the clustered WSNs by reducing the transmission overhead. Their technique consisted two consecutive models: Data Prediction (DP) by Bi-directional Long Short-Term Memory (Bi-LSTM) and Data Compression (DC) employed Probabilistic Principal Component Analysis (P-PCA). Lalit Kumar and Pradeep Kumar [33] developed the Beet Swarm Induced Tunicate Algorithm (BITA), a hybrid of Beetle Swarm Optimization (BSO) and Tunicate Swarm Algorithm (TSA), to acquire optimum CH selection based on multi-objective criteria.

Rani et al. [34] designed a model to select optimal CHs from a group of nodes by integrating Ant Colony Optimization (ACO) with an Improved Social Spider Cluster Optimization Algorithm (ISSOA). They also applied Optics-Inspired Optimization (OIO) to determine routes between selected CHs and base station.

Harmeet Singh et al. [35] focused on mitigating wormhole attacks in clustered WSNs for IoT by developing an ACO-based trust method. Their model calculated direct trust of nodes which depended on pheromone concentration rather than the packet forwarding behavior, thereby helping to avoid packet loss.

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Archita Bhatnagar et al. [36] developed Exponentially-Enhanced Whale-Differential Evolution Optimization (E-WDEO) to enhance network lifetime and performance. The developed algorithm was processed on two stages, initially cluster heads were selected through Differential Evolution (DE) and Whale Optimization Algorithm (WOA), ensured better resource distribution

Sagar Mekala et al. [37] employed Termite Queen and Artificial Fish Swarm Optimization Algorithm (TQAFSOA) based clustering and routing in mobile sink to minimize the limitations of unequal clustering, utilization of gateways and multi-hop communication to enhance network lifetime. For addressing the traditional drawbacks of clustering and process problems, Termite Queen Optimization (TQO) was employed. Then, scheduling and routing to fitness of energy effective path among CHs and mobile sink to enhance the network lifetime. Artificial Fish Swarm Optimization Algorithm (AFSOA) addressed primary problems on conventional clustering and routing approaches through unequal clustering from CHs to sink nodes. The table 1 represents summary table of existing algorithms.

Table 1 Summary Table of Existing Algorithms

Authors	Algorithms used	Fitness function	Advantages	Limitations
Rekha and Garg [21]	K-LionER	Residual energy, Distance, ICC	Enhances network lifetime and energy efficacy	Sensitive to initial clustering, less efficient in large-acle networks
Roberts and Ramasamy [22]	HPC-SRP	Residual energy, Distance	Secure data transfer, attacker surveillance	Higher communication overhead, minimized scalability
Verma and Jha [23]	MUMLP + BSP-GSA	Residual energy, Delay, Distance	Provide secure data broadcasting	High computational complexity, slower convergence
Tan and Nguyen [24]	EERHA	Residual energy, EWC and distance	Minimize communication costs and better clustering	Needs large iterations for stability, delay increases with several nodes
Vazhuthi et al. [25]	ANFIS-ROA	Residual energy, Distance	Enhances QoS with fault management	Computationally expensive, limited scalability
Priyanka et al. [26]	Region-based RCHS + SRLC	Residual energy, Distance	Improves energy efficacy in agricultural IoT	Limited generalization across particular domains
Bhukya Suresh and Prasad [27]	Improved LEACH	Node coverage, Energy consumption rate, Distance to BS	Stable CH selection and energy efficacy	Sensitive to node density, limited scalability
Mehra et al. [28]	LBECR	Fuzzy variables (energy, distance, node coverage)	Better load balancing	Increased rule complexity leads to energy depletion
Nevine Makram Labib et al. [29]	ETSDEEC	Soft threshold, Residual energy	Minimizes unnecessary transmissions	Threshold design complexity, not adaptive to mobility
Javadpour et al. [30]	Fuzzy clustering + Particle Optimization	Initial CH scoring, Residual energy	Better cluster formation accuracy	Overfit to local optima, slower convergence
Singh and Anand [31]	Hybrid Fuzzy C-means + GWO	Residual energy, Distance	Improves clustering robustness	Computational overhead increases with node size

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Pandey et al. [32]	Bi-LSTM + P-PCA	Distance, Energy, and Latency	Minimizes transmission overhead	Needs high processing power, not lightweight
Lalit Kumar and Pradeep Kumar [33]	BITA	Multi-objective: Energy and Distance	Enhanced CH selection stability	Complexity increases with swarm size
Rani et al. [34]	ACO + ISSOA + OIO	Residual energy, distance, coverage	Provides adaptive CH and secure routing	High convergence time and complex integration
Harmeet Singh [35]	ACO-based Trust Model	Trust values, Residual energy	Detects wormable attacks, enhances reliability	Additional computation for trust estimation
Archita Bhatnagar et al. [36]	E-WDEO (Whale + DE)	Distance, Energy, Latency	Improves convergence stability, minimizes latency	Hybrid complexity increases runtime
Sagar Mekala et al. [37]	TQAFSOA	Distance, Energy, Latency	Handles unequal clustering, supports mobile sink	No formal fitness evaluation, scalability not proven

The drawbacks identified from the existing research are noted as follows: inadequate fitness function, high energy utilization and routing without clustering. This study ensures that the suitable objective metrics are utilized with ECM-POA for ensuring efficient clustering and routing to minimize the energy utilization of an entire network. The proposed ECM-POA algorithm improves conventional POA by iterating the Cauchy mutation mechanism, enables good exploration and avoidance of local optima on clustering and routing tasks. It utilizes the multi-objective fitness function which considers residual energy, intra-to-inter cluster distance, node density and intra-cluster communication cost for ensuring the energy-efficient and balanced CH selection. The biologically inspired predator-prey dynamics simulating exploration and exploitation stages, when Cauchy mutation introduced adaptive variation. These characteristics enhances convergence stability, energy efficacy and network lifetime outperformed the existing metaheuristic algorithms in WSN-assisted IoT environments.

2.1. Model Selection

The proposed ECM-POA is chosen based on the requirement to mitigate the challenges of traditional clustering and routing algorithms in WSN-IoT. The conventional algorithms such as LEACH, PSO and WOA suffered from poor global search ability, early convergence and an ineffective energy distribution because of the random CH selection strategies. To address these limitations, POA is selected because of its balance among exploration and exploitation, allows it to perform adaptive updates and intelligent pathfinding. To improve exploration ability and prevent premature convergence, the Cauchy mutation mechanism is incorporated into POA. This incorporation introduced the controlled randomness for search dynamic, which helps to escape local optima and ensures search of solution space. The integrated ECM-POA model helps in optimal CH selection and energy-efficient routing by multi-objective fitness function that includes residual energy, intra-to-inter cluster distance, node density and intra-cluster communication cost (ICC). These parameters get assigned with energy conservation, prolonged network lifetime and reduced communication overhead in WSN-IoT environments. When Compared with the existing algorithms, the ECM-POA provides superior adaptability, convergence rate and robustness under varying node densities and network sizes.

3. PROPOSED SECTION

In this manuscript, the efficient data broadcasting is attained through an ECM-POA-enabled optimum CH selection and route path selection on WSN-IoT. The energy utilization of the sensors is reduced by creating a clustering mechanism with data broadcasting through ECM-POA. The minimization of energy consumption helps to enhance the life expectancy of sensors, resulting in high data delivery. Figure 1 represents process of the energy-efficient clustering and routing algorithm.

3.1. Sensor Initialization

The nodes are randomly deployed on the WSN-IoT, with ECM-POA used selected CHs. Then, clusters are formed in WSN-IoT after CHs are chosen from the network. Next, a route from the transmitting CH to the BS receiver is identified by ECM-POA. The optimum CH and route path selection are defined in following sections.

3.2. Selecting Optimum CH by ECM-POA

ECM-POA is utilized to identify the optimum CHs from the sensors of WSN-IoT. The POA is imitated depended on behavior of a pufferfish. The primary difference between POA and ECM-POA is that the ECM-POA incorporates the

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Cauchy mechanism to enhance the global search capability to obtain better optimum solutions. Next, ECM-POA is applied to select the optimum CHs from the sensors.

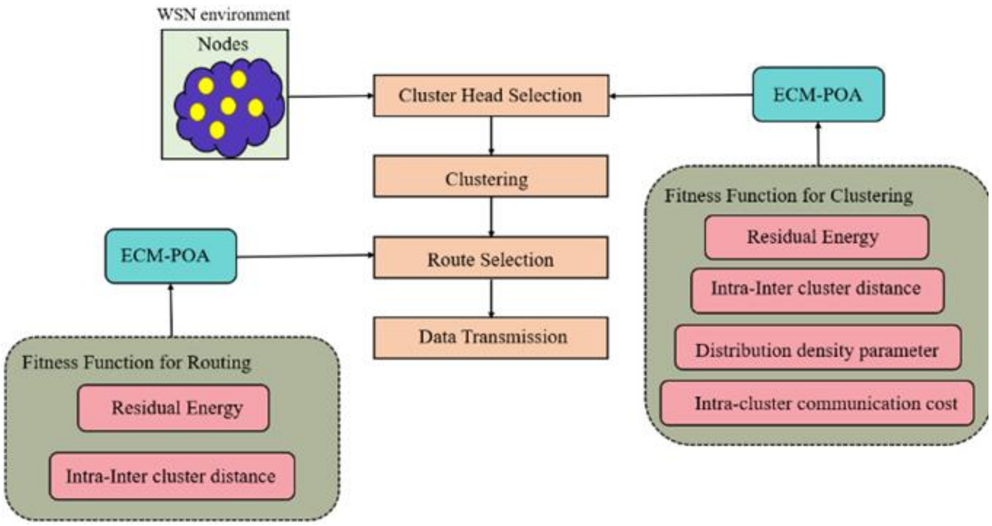

Figure 1 Process of Energy-Efficient Clustering-Based Routing Algorithm

3.3. Representation and Initialization

In the initial solution of ECM-POA, the pufferfish defines group of sensor nodes which are chosen as potential CHs. Here, each pufferfish is initialized with the ID of random node among 1 and N, where N is total number of nodes in WSN-IoT. The ith pufferfish of ECM-POA is defined as $X_i = (X_{i,1}, X_{i,2}, \dots, X_{i,dim})$, where dim represents the dimension of each pufferfish as the number of CHs.

3.3.1. Iteration Process

The POA is a population-based algorithm which obtains efficient solutions for the optimization issues through their population search energy on the problem-solving areas during an iteration procedure. Every member of POA defines the scores for decision variables of issue based on their location in the search area. Hence, every member of POA is a candidate solution to the issue, which is modelled from the mathematical point by vector, where every component of the vector is respective to the decision variable. The members of POA together form algorithm population. The community of these vectors is designed through matrix, as shown in Equation (1). The initial position of every member of POA in an initial phase of algorithm is initialized by Equation (2).

$$X = \begin{bmatrix} X_1 \\ \vdots \\ X_i \\ \vdots \\ X_N \end{bmatrix}_{N\times m} = \begin{bmatrix} x_{1,1} & \cdots & x_{1,d} & \cdots & x_{1,m} \\ \vdots & \ddots & \vdots & ⋰ & \vdots \\ x_{i,1} & \cdots & x_{i,d} & \cdots & x_{i,m} \\ \vdots & ⋰ & \vdots & \ddots & \vdots \\ x_{N,1} & \cdots & x_{N,d} & \cdots & x_{N,m} \end{bmatrix}_{N\times m} \quad (1)$$

$$x_{i,d} = lb_d + r \cdot (ub_d - lb_d) \quad (2)$$

In the above Equation (1), X is population matrix of POA, X_i represents ith member of POA, $x_{i,d}$ represents dth dimension on search area, N is count of population members, m represents number of decision variables, r represents the random number on range [0,1], lb_d and ub_d represents lower and upper bounds of dth decision variable.

With every member of POA considered candidate solution for issue, the fitness function of issue is evaluated. The group of estimated scores for an objective function of an issue is described by a vector, as given in Equation (3).

$$F = \begin{bmatrix} F_1 \\ \vdots \\ F_i \\ \vdots \\ F_N \end{bmatrix}_{N\times 1} = \begin{bmatrix} F(X_1) \\ \vdots \\ F(X_i) \\ \vdots \\ F(X_N) \end{bmatrix}_{N\times 1} \quad (3)$$

In the above Equation (3), F is vector of an estimated fitness function and F_i represents estimated objective function which depended on the ith member of POA.

In every iteration, the location of population candidates of POA is updated on two stages, where the first exploration depends on predator's attack simulation using pufferfish and second, the exploitation depends on the defense mechanism that is simulated on the pufferfish against a predator.

3.3.2. Exploration stage (Predator Attack towards Pufferfish)

In an initial stage of POA, the location of the population members is updated by depending on the simulation strategy of the predator attacks on pufferfish. Due to their slower speed, pufferfishes are feasible prey to hungry predators. The location changes of the predator in an attack on a pufferfish

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are simulating to update the locations of POA members in a problem-solving area. Modeling the predator movements toward pufferfish causes significant changes in the locations of the POA members, thereby improving the exploration ability of an algorithm and maximizing the energy efficiently during the global search. In designing the POA, every population member acts as a predator, and the location of different population members holds a good value for fitness function taken for the location of a candidate pufferfish to attack. Group of pufferfish which is assigned to every population member is defined by Equation (4).

$$CP_i = \{X_k : F_k < F_i \; and \; k \neq i\},$$
$$where \; i = 1,2, \dots, N \; and \; k \in \{1,2, \dots, N\} \qquad (4)$$

In above Equation (4), CP_i is a group of candidate pufferfish positions for ith predator, X_k represents a population candidate with the best fitness function score than ith predator, and F_k represents the objective function score. In the developing POA, it is presumed that in all candidate pufferfish gets defined in CP group, the predator chooses the pufferfish randomly that is designed as a chosen pufferfish. Based on the predator movement towards a pufferfish, a new location in an issue-resolving area is measured for every member of POA, as shown in Equation (5). Next, when4. fitness function is enhanced in new location, this new location replaces past position of respective member, as in Equation (6).

$$x_{i,j}^{P1} = x_{i,j} + r_{i,j} \cdot \left(SP_{i,j} - I_{i,j} \cdot x_{i,j}\right) \qquad (5)$$

$$X_i = \begin{cases} X_i^{P1}, & F_i^{P1} \leq F_i \\ X_i, & else \end{cases} \qquad (6)$$

In the above Equations (5) and (6), SP_i represents chosen pufferfish for ith predator which was chosen randomly from CP_i set, $SP_{i,j}$ represents their jth dimension, X_i^{P1} represents new position measured for ith predator based on initial stage of POA, $x_{i,j}^{P1}$ represents their jth dimension, F_i^{P1} defines objective function score, $r_{i,j}$ defines random members within a range [0,1] and $I_{i,j}$ represents the randomly chosen number.

3.3.3. Exploitation Stage

In the next stage of POA, the location of the population members is updated by depending on the defense mechanism of pufferfish which is simulated against the predator attacks. When pufferfish are attacked through the predator, they inflate their elastic stomach with water, transforming into ball covered with pointed spines. When the predator encounters a warning instead of a viable opportunity, it retreats from the location of the pufferfish, causing slight changes in a location of POA members. This adapted behavior enhances the exploration ability of an algorithm in the local search phase. By depending on the model of predator's location changing while moving away, a new location is measured to every member of POA by Equation (7). Next, the new location is evaluated to determine whether it maximizes the objective function score and is updated based on Equation (8). While assessing the new location for a POA member, the objective function scores are compared to verify that if the new location provides a good solution to the problem. If a result is positive, then a new location is accepted to the respective member of POA; otherwise, new location is considered as irrelevant, and the respective member remains at its previous location. Hence, Equation (8) represents the update process for every member of POA, aimed at improving objective function score.

$$x_{i,j}^{P2} = x_{i,j} + \left(1 - 2r_{i,j}\right) \cdot \frac{ub_j - lb_j}{t} \qquad (7)$$

$$X_i = \begin{cases} X_i^{P2}, & F_i^{P2} \leq F_i \\ X_i, & else \end{cases} \qquad (8)$$

In the above Equations (7) and (8), X_i^{P2} is new position measured for ith predator based on next stage of POA, $x_{i,j}^{P2}$ represents jth dimension, F_i^{P2} is objective function score, $r_{i,j}$ represents random number within range [0,1] and t represents iteration number.

3.3.4. Cauchy Mutation Mechanism

Cauchy mutation mechanism is an iterative process that aims to improve the exploration capability of a local search in POA, thereby reducing the tendency to get trapped in local optima. By employing a Cauchy mutation mechanism for individuals in the POA population, the algorithm becomes more efficient in identifying the global optimum solution.

This mechanism uses the one-dimensional density function, which guides the algorithm towards the high probability of identifying the global optimal solution. Its mathematical expression is given by Equation (9).

$$f(x, \, x^0, \, \gamma) = \left(\frac{1}{\pi\gamma}\right) \times \left(\frac{\gamma^2}{(x - x^0)^2} + \gamma^2\right) \qquad (9)$$

In the above Equation (9), x is the mutated parameter when x^0 and γ represent the position and scale parameters respectively. This mechanism introduces the diversity and balance in the exploration and exploitation phases, thereby mitigating the stability problems and premature convergence in traditional algorithms.

3.4. Fitness Function

The fitness functions considered in this manuscript for selecting an optimum CHs are: average residual energy $C_{F1}(i)$, Intra to Inter distance $C_{F2}(i)$, distribution density parameter $C_{F3}(i)$ and Intra-cluster Communication Cost (ICC) $C_{F4}(i)$. All these fitness functions are concatenated with each other and converted to one fitness function, and its mathematical expression is given in Equation (10).

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$$C_F = \omega_1 \times C_{F1}(i) + \omega_2 \times C_{F2}(i) + \omega_3 \times C_{F3}(i) + \omega_4 \times C_{F4}(i) \quad (10)$$

In the above Equation (10), $\sum_{i=1}^{4} \omega_i = 1$, $\omega_i \in (0,1)$, while $\omega_1, \omega_2, \omega_3$ and ω_4 represent the weights corresponding to each fitness function.

3.4.1. Average Residual Energy

Average residual energy describes mean residual energy of active sensors on ith cluster in jth round, which are essential for CH selection. This fitness function ensures that the energy depletion is balanced in a cluster, primary consideration as CHs generally utilize significant energy than other nodes.

This algorithm maintains the network's energy efficacy and durability through avoiding the energy degradation on CHs. This parameter is used to measure the weighted factor of a residual energy, which is significant for an effective energy management in network. Its mathematical expression is given in Equation (11).

$$C_{F1}(i) = \frac{E_{res}(i)}{CE(i,j)} \quad (11)$$

3.4.2. Intra to Inter Distance

This function effectively influenced the total energy consumption in a network. Shorter communication distance results in lower energy utilization. Hence, this parameter is used as the main metric and its mathematical expression is given as Equation (12).

$$C_{F2}(i) = 1 - \frac{d(i,sink)}{TD(i)} \quad (12)$$

In the above Equation (12), $d(i, sink)$ is distance between ith and sink nodes.

3.4.3. Distribution Density Parameter

Distribution Density Parameter coefficient for ith node determines a number of sensor nodes in radius, which is essential to choosing CHs in the cluster. This parameter is significant to understand the node density and cluster effectiveness, and its mathematical expression is given in Equation (13).

$$C_{F3}(i) = \frac{den\ (i)}{TD\ (i)} \quad (13)$$

3.4.4. Intra-Cluster Communication Cost (ICC)

Nodes consume energy while communicating with other nodes that are located at a certain distance. Every member on the cluster forwards their information to the CH, then the CH forwards it further.

Energy consumption gets maximized with distance to communicate with nodes and its mathematical expression is given in Equation (14).

$$C_{F4}(i) = \sum_{k=1}^{n} \left(\frac{\sum_{j=1}^{m} ED\left(CH_k \rightarrow CM_{k,j}\right)}{m} \right) \quad (14)$$

In the above Equation (14), $CM_{k,j}$ represents jth member node of kth cluster and m is count of members on cluster.

3.5. Cluster formation

After choosing CHs by ECM-POA, the cluster members are assigned to their corresponding CHs. Residual energy and distance are measured on potential function for cluster formation, and its mathematical expression is given in Equation (15).

$$Potential\ function\ (N_i) = \frac{E_{CH}}{dis(N_l, CH)} \quad (15)$$

3.6. Route Path Identification by ECM-POA

After clustering is performed within the network, routes among transmitted CH and receiver BS are identified by ECM-POA. The initial weight of every path is measured by the distance among nodes. The fitness function for ECM-POA considers the residual energy and intra to inter distance, as defined in Equation (16).

$$RF = \omega_1 \times \frac{E_{res}(i)}{CE(i,j)} + \omega_2 \times 1 - \frac{d(i, sink)}{TD(i)} \quad (16)$$

In the above Equation (16), ω_1 and ω_2 denote the weight parameters that are employed for objective values in route path identification. Failure node is avoided by using the residual energy, while the distance minimizes energy consumption by producing route paths with lesser broadcasting distance.

The proposed ECM-POA is developed by an integration of Cauchy mutation mechanism with POA. The development process includes three major stages such as sensor node initialization and CH selection using ECM-POA, cluster formation based on residual energy and intra-cluster distance and at last route path selection using a multi-objective fitness function.

Unlike traditional algorithms that relies on random CH selection, the ECM-POA introduces Cauchy-based mutation strategy to enhance global search and prevents premature convergence. This adaptation ensures good exploration of solution space and enhanced robustness on highly dense WSN-IoT networks.

Additionally, multi-objective fitness function considers residual energy, intra-to-inter cluster distance, node density and intra-cluster communication cost, offers more holistic optimization algorithm compared to the existing algorithms. The detailed workflow of proposed ECM-POA is described in Algorithm 1.

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Input – N is count of sensor nodes, Max_{iter} is maximum number of iterations, PopSize is number of pufferfish (population), Fitness () is an objective function with residual energy, distance, node density and ICC.

Output – Optimum CH and route paths

Initialize sensor nodes with random position and energy levels

Initialize population of pufferfish with random node IDs

Evaluate the fitness for every pufferfish using residual energy, Intra to Inter-Cluster distance, Node distribution density and Intra-cluster Communication Cost (ICC).

For $iter = 1\ to\ Max_{iter}$ do

For every pufferfish i

Perform exploration

- Choose best solution randomly
- Update position using movement rules
- If new position enhances fitness, then position is updated

Perform exploitation

- Simulate inflation from predator
- Adjust position to refine solution
- If new position enhances fitness, then position is updated

Employ Cauchy mutation to improve exploration

- Mutate present position using Cauchy distribution
- Retain mutated position if fitness is enhanced

Choose optimum CHs based on better pufferfish solution

From clusters depended on residual energy and distance to CHs

For every CH, identify optimum routing path to BS using ECm-POA

- Optimize route using fitness based on residual energy of relay nodes and distance to BS

Return chosen CHs and route paths

Algorithm 1 ECM-POA for Optimum CH and Routing Path Selection

4. EXPERIMENTAL RESULTS

Performance of ECM-POA is simulated in MATLAB R2020 b environment with system configurations being i5 processor, 8GB RAM and Windows 10 (64 bit). Evaluation parameters of throughput, alive nodes, residual energy and delay are considered for the performance evaluation of the developed ECM-POA algorithm. The existing algorithms namely, Grey Wolf Optimization (GWO), Whale Optimization Algorithm (WOA), Particle Swarm Optimization (PSO) and traditional POA, are considered for the performance evaluation. Table 2 displays the simulation parameters of the model.

Table 2 Simulation Parameters

Parameters	Values
Network size	1000×1000 m
Number of nodes	100 – 500
Initial energy	0.5 J
Data packet size	4000 bits
Population size	30
Maximum iteration	100

4.1. Throughput Analysis

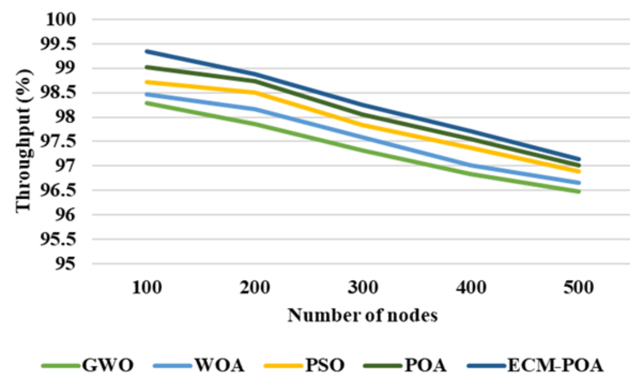

Figure 2 Throughput vs Number of Nodes

In Figure 2, the model's network throughput performance is evaluated for a varied number of nodes. Throughput calculates the total amount of data which is successfully delivered to BS over time. The ECM-POA improves the CH selection and routing efficacy, that facilitates better bandwidth usage and continuous data flow, thereby enhancing the overall network throughput. The developed ECM-POA is designed for lesser communication overhead on sensor nodes to achieve reliable routing. By incorporating the distribution density parameter, the developed ECM-POA offers a reliable transmission technique for data broadcasting than the existing algorithms. When compared to the existing algorithms, the network throughput is increased for the developed ECM-POA.

4.2. Alive Node Analysis

In Figure 3, performance of alive nodes is evaluated with several nodes. This metric represents number of functioning nodes throughout network lifecycle. The use of ECM-POA ensures optimal CH selection and balanced load distribution, that minimizes the chances of early node death. The higher count of alive nodes over time shows that a proposed model efficacy in extending network lifetime. The retransmission of data minimizes the network's performance in dynamic tracking, causing nodes to lose energy, resulting in a high number of dead nodes.

Efficacy of routing protocol is calculated through how accurately data is delivered to their intended destination. The network lifetime is directly associated to number of alive nodes, and therefore, an efficient algorithm is required to ensure the optimal data transmission at a shorter period of time. This enables network to function with greatest number of alive nodes, as opposed to existing algorithms.

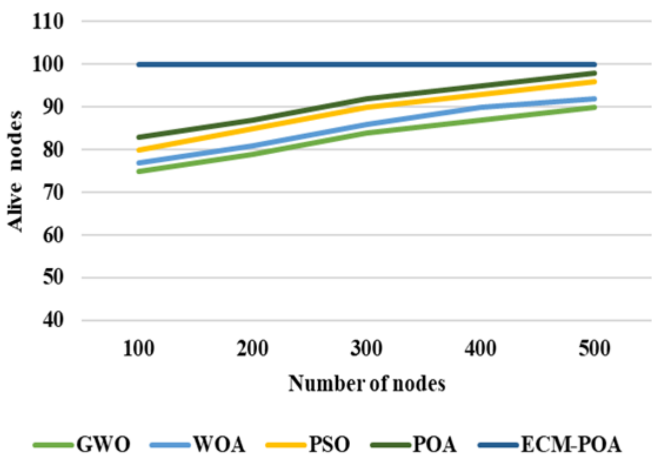

Figure 3 Alive Nodes vs Number of Nodes

4.3. Residual Energy Analysis

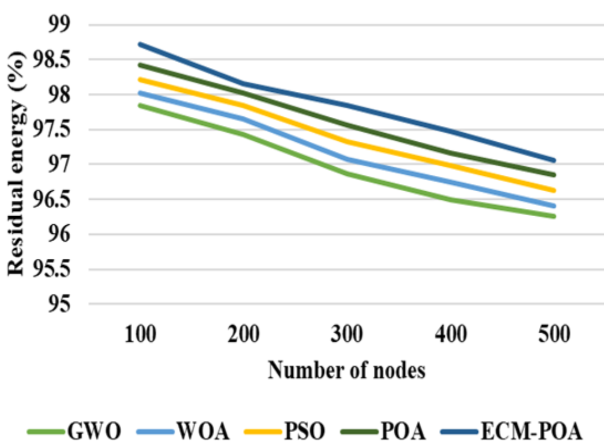

Figure 4 Residual Energy vs Number of Nodes

In Figure 4, the model's residual energy is evaluated with a varied number of nodes. This metric plays crucial role in determining lifetime of a network. Residual energy is energy left in node after data processing, aggregation and distribution. A higher level of residual energy ensures that the network remains active during data broadcasting. Residual energy reflects remaining energy in sensor nodes after every communication round. ECM-POA is developed with multi-objective fitness function that incorporated energy balancing, this metric directly validates the model's capability to reduce energy consumption and avoid rapid energy depletion, particularly in CH nodes. The proposed network is left with higher residual when compared to existing algorithms.

4.4. Delay Analysis

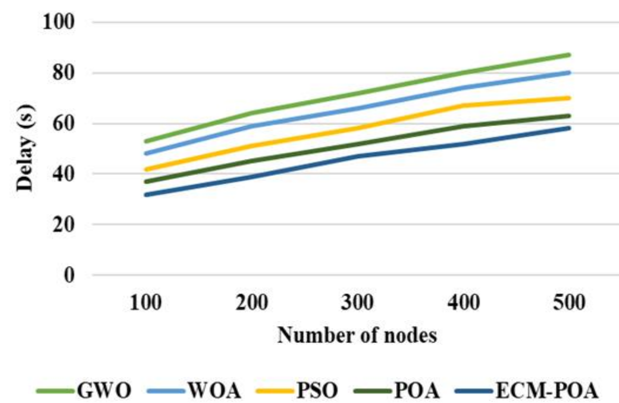

Figure 5 Delay vs Number of Nodes

In Figure 5, the model's delay is evaluated against the number of nodes. These metric measures time required to position the BS and broadcast data. ECM-POA optimizes the routing paths through reducing intra-cluster communication cost and hop count, that minimizes congestion and ensures timely delivery, ensures less delays. While the BS moves, the connected devices are relocated to newer positions by following the initially recommended algorithm.

As a result, the source transmits data packets to nearest coordinating device during data transmission. Delay minimizes when a path is predefined, and newer paths are evaluated when the devices die to minimize the time consumed to restore a service.

However, this approach requires knowledge of the BS location, which results in increased delay. However, compared to the existing algorithms, the proposed network has a lower delay in data broadcasting.

4.5. Comparison Results

Table 3 Different Simulation Scenarios

Parameters	Scenario 1	Scenario 2	Scenario 3
Number of nodes	100	100	50 – 250
Initial energy (J)	0.3	2	3
Packet size (bits)	2000	64	150 m

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Table 4 Comparative Analysis with K-LionER

Methods	Metrics	Number of rounds				
		200	400	600	800	1000
K-LionER [16]	Alive nodes	100	100	100	100	100
Proposed ECM-POA		100	100	100	100	100

Table 5 Comparative Analysis with K-LionER

Methods	FND	HND	LND
K-LionER [16]	1425	1439	1449
Proposed ECM-POA	1456	1471	1485

Table 6 Comparative Analysis of HPC-SRP

Methods	Number of Nodes	Residual Energy (J)	Throughput (%)	Delay (ms)
HPC-SRP [17]	100	97.26	98.06	0.10
Proposed ECM-POA		98.17	98.63	0.08

Table 7 Comparative Analysis of MUMLP

Metrics	Methods	50	100	150	200	250
Throughput (kbps)	MUMLP [18]	256	245	232	222	215
	Proposed ECM-POA	277	261	247	232	228
Delay (ms)	MUMLP [18]	5.1478	7.8541	9.5478	12.1478	14.6412
	Proposed ECM-POA	5.0327	7.5205	9.1082	11.8724	13.4217

In this section, performance of developed ECM-POA is compared to the existing algorithms: K-LionER [16], HPC-SRP [17] and MUMLP [18] for different simulation scenarios. Table 2 represents the different simulation scenarios used in existing algorithms. The table 3 represents the different simulation scenarios of existing models. Tables 4 and 5 display the performance of the developed ECM-POA compared to existing algorithms: K-LionER [16] with number of rounds with metric alive nodes. Table 5 represents the evaluation results for First Node Die (FND), Half Node Die (HND) and Last Node Die (LND). Table 6 displays the performance of the developed ECM-POA compared to the existing HPC-SRP [17] in terms of residual energy, throughput and delay. In Table 7, performance of developed ECM-POA is compared to existing MUMLP [18] in terms of throughput and delay.

4.6. Discussion of Results

The performance evaluation determines that the proposed ECM-POA consistently outperforms the traditional clustering and routing algorithms in WSN-IoT environments. The comparative analysis across several metrics like throughput, alive nodes, residual energy and delay, shows a superiority of a proposed method.

Initially, in terms of throughput, the ECM-POA obtains higher data delivery rates across all the network sizes comparing with GWO, WOA, PSO and conventional POA. This enhancement is from their ability to balance the residual energy and node distribution density, thereby minimizing the packet loss and maintaining continuous flow of the data even in dense networks. The alive node analysis shows that the ECM-POA extends the network lifetime by delaying FND, HND and LNS when comparing with K-LionER Balanced energy distribution obtained by Cauchy mutation mechanism that prevents early depletion of particular CHs, ensures that the huge ratio of nodes remains significant throughout the simulation rounds.

In terms of residual energy, the ECM-POA consistently maintains higher energy level across all scenarios. While

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comparing with an existing algorithm, the proposed algorithm preserves more residual energy, thereby validating their effectiveness in reducing the unnecessary energy dissipation. This effective energy management translates into large operational periods and enhanced sustainability for large-scale WSN-IoT deployments.

The delay analysis shows that the ECM-POA obtains lower latency when compared to the other existing algorithms. By reducing intra-cluster communication costs and optimizing routing paths, ECM-POA minimizes congestion and ensures timely packet delivery. This advantage is specifically essential for latency-sensitive IoT applications. Overall, the integration of Cauchy mutation mechanism with POA enables ECM-POA to mitigate the limitations of previous algorithms such as premature convergence, random CH selection and high communication overhead. The utilization of multi-objective fitness function ensures balanced residual energy, distance, node density and communication cost. These algorithms improve the network throughput, increase node survivability, extends network lifetime and reduce communication delay.

4.7. Research Implication

The proposed ECM-POA model introduced the novel and adaptive algorithm for clustering and routing in WSN-assisted IoT, addressed issues such as energy imbalance, limited scalability and premature convergence in conventional algorithms. This integration of Cauchy mutation mechanism with biologically inspired POA improves exploration and solution diversity effectively, thereby leads to much stable and energy-efficient communication structures. Additionally, usage of multi-objective fitness function ensures more holistic optimization strategy which considers the longevity of the network, communication cost and load distribution.

5. DISCUSSION

The developed ECM-POA effectively enhances the clustering and routing efficacy in WSN-assisted IoT environments by including a Cauchy mutation mechanism to improve global optimization. The use of multiple fitness functions ensures optimal CH and route path selection, which increases throughput, lowers delay, and maximizes the network lifetime. The experimental results show that ECM-POA consistently outperforms existing algorithms such as K-LionER [16], HPC-SRP [17], and MUMLP [18] under different network sizes and configurations. Its ability to maintain high residual energy and node availability validates its suitability for large-scale, energy-constrained IoT applications. Additionally, the approach achieves balanced energy utilization across network through effectively selecting the CHs based on the residual energy and network topology parameters. The combination of exploration and exploitation strategies in POA improves the convergence speed and avoids premature optimization traps. By dynamically adapting to network changes, the ECM-POA helps to maintain stable and reliable data transmission under high node density. These advantages highlight its potential in IoT systems requiring scalable and energy-aware communication protocols.

The enhanced residual energy preservation and higher number of alive nodes over simulation round represents energy-aware nature of ECM-POA. By avoiding overburdening of the specific nodes, the algorithm promotes a fair energy distribution, by delaying FND and LND occurrences. The high PDR and increased throughput show the algorithm's robustness in maintaining reliable data broadcasting, even as node density scales. This shows the effectiveness of routing strategy in avoiding congested or unreliable routes. Additionally, the algorithm obtains less end-to-delay, that is essential for latency-sensitive IoT applications like healthcare monitoring.

The Cauchy mutation shows the effectiveness in introducing the essential perturbation to avoid local optima faced by the conventional POA. This proposed algorithm contributes to the enhanced convergence speed and ensures that the algorithm does not stagnate prematurely in the optimization process. Furthermore, biologically inspired exploration-exploitation mechanism simulates the predator-prey behavior, support to balance the global and local search causes consistent better solution across dynamic WSN environments.

5.1. Limitations

The major limitation of the developed ECM-POA is its assumption that the sensor nodes remain static throughout the network operation. This restricts its applicability in mobile WSN environments, where nodes frequently change positions due to dynamic deployment scenarios. The static assumption limits the algorithm's ability to adapt to topology changes in real time, which degrades the quality of clustering and routing decisions. Moreover, the computational complexity of ECM-POA increases as the network size grows. Since the algorithm relies on iterative optimization processes, including exploration, exploitation, and fitness evaluation across multiple dimensions, large networks require significant processing time and memory, hindering scalability in resource-constrained systems.

6. CONCLUSION

Clustering algorithms tend to consume significant energy and keep network nodes active for long periods. Conventional protocols often rely on the random probability of CH selection. Primary aim is to extend the network lifetime by enhancing the CH selection algorithm. In this manuscript, the ECM-POA is developed for an optimal CH and route path selection. Cauchy mechanism is included into traditional POA to enhance global search ability for more effective CH and route path selection. Fitness functions like residual energy, intra-to-inter cluster distance, distribution density, and intra-

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cluster communication costs are considered to select optimal CHs. Clusters are then formed using a potential function. Afterward, shorter communication distances are selected by using the developed ECM-POA that depended on fitness functions of residual energy and intra-to-inter cluster distance. The developed ECM-POA achieves the highest network throughput of 99.34% for 100 nodes, 98.87% for 200 nodes, 98.26% for 300 nodes, 97.71% for 400 nodes, and 97.15% for 500 nodes, when compared to the existing algorithms. In future work, ECM-POA can be extended to support mobility-aware clustering for dynamic WSN environments. Different meta-heuristic algorithms can be explored to further enhance network lifetime in WSN-IoT. Moreover, minimizing computational overhead through lightweight optimization strategies will improve scalability for large-scale IoT deployments.

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