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# DCOR: Enhancing Network Lifetime and Performance in IoT-Based Wireless Sensor Networks through Distributed Clustering and Optimized Routing

**Vaibhav V. Deshpande[1] and Dr. Rajesh K. Shukla[2]**

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**Abstract:** The burgeoning field of Internet of Things (IoT) necessitates efficient management of network resources, particularly in Wireless Sensor Networks (WSNs), to extend network lifetime and enhance communication performance. Existing clustering and routing mechanisms in WSNs often grapple with limitations like suboptimal path selection, high energy consumption, and inconsistent communication speeds, which significantly impede network reliability and longevity. This study introduces a novel approach to surmount these challenges, focusing on enhancing network lifetime and performance in IoT-based WSNs through a Distributed Clustering Mechanism (DCM) and an efficient routing algorithm, the Teacher Learner Firefly Optimizer (TLFFO). Our proposed model incorporates spatial node metrics (node location, residual energy, and energy model) to form optimized clusters. These clusters, leveraging temporal node metrics such as previous communication performance, enable the establishment of multipath routes. The TLFFO, a custom-developed algorithm, innovatively integrates the principles of teacher-learner-based optimization with the bio-inspired firefly algorithm, ensuring optimal route selection with a focus on energy efficiency and communication speed. Empirical evaluations reveal that our model outperforms existing clustering and routing methods, demonstrating a 6.5% increase in communication speed, an 8.5% enhancement in energy efficiency, a 3.2% rise in throughput, along with a significant reduction in jitter (4.9%) and an improvement in packet delivery performance (4.9%). These advancements underscore the potential of our approach in extending the network lifetime while maintaining high-quality communication standards in IoT-based WSNs. The implications of this work are profound, promising a transformative impact on the efficiency and sustainability of WSNs in IoT environments. By addressing the critical challenges of energy consumption and communication efficacy, our approach sets a new benchmark for future research and practical applications in the domain of wireless sensor networking operations.

***Keywords:*** *Wireless Sensor Networks, Internet of Things, Distributed Clustering, Routing Optimization, Teacher Learner Firefly Optimizer*

## 1. Introduction

The advent of the Internet of Things (IoT) has heralded a new era in the digital world, revolutionizing the way devices communicate and interact with each other. At the heart of this technological transformation are Wireless Sensor Networks (WSNs), which serve as the foundational infrastructure for IoT applications. These networks comprise numerous sensor nodes, each capable of collecting and transmitting data across the network. However, the inherent limitations of these sensor nodes, particularly in terms of energy resources and computational power, pose significant challenges in network management, particularly in extending the network's lifetime while maintaining optimal performance [1, 2, 3].

Existing methods in WSNs primarily focus on clustering and routing techniques to manage these challenges. Clustering involves grouping sensor nodes into clusters, each managed by a cluster head, to streamline data transmission and reduce energy consumption. However, traditional clustering methods often fail to consider the dynamic nature of sensor nodes, leading to suboptimal cluster formation and increased energy expenditure. Similarly, conventional routing techniques, while aiming to find the shortest path for data transmission, frequently overlook the crucial aspects of energy efficiency and network traffic load, resulting in premature network degradation and inconsistent communication performance [4, 5, 6].

Recognizing these gaps, this paper introduces a novel approach that integrates a Distributed Clustering Mechanism (DCM) with an advanced routing algorithm, the Teacher Learner Firefly Optimizer (TLFFO). Our approach is built upon the premise that an effective WSN management strategy must consider both spatial and temporal metrics of sensor nodes. Spatial metrics, such as the location of nodes, their residual energy, and energy consumption models, are crucial in forming energy-efficient clusters. In contrast, temporal metrics, particularly nodes' past communication performance, play a vital role in establishing robust and reliable routing paths.

[1]*Oriental University, Indore, MP 453555, India*
*vdeshpande2074@gmail.com*
[2]*Oriental University, Indore, MP 453555, India*
*shukladrrajeshk@gmail.com*

The TLFFO, at the core of our routing strategy, is a hybrid algorithm that combines the strengths of teacher-learner-based optimization and the bio-inspired firefly algorithm. This combination allows for a more nuanced and adaptive approach to routing, effectively balancing the trade-offs between path length, energy consumption, and network traffic loads. Our approach not only optimizes the energy consumption across the network but also ensures high-quality communication standards, addressing the critical challenges of jitter, throughput, and packet delivery performance.

The introduction of this innovative clustering and routing methodology in IoT-based WSNs marks a significant advancement in the field. By holistically addressing the limitations of existing methods and focusing on the dual objectives of extending network lifetime and enhancing communication performance, our approach sets a new benchmark for future developments in WSN management. This paper aims to detail the design, implementation, and empirical evaluation of our model, demonstrating its superiority over existing techniques and its potential impact on IoT applications reliant on WSNs.

**Motivation & Contribution**

The motivation for this research stems from the critical need to address the inherent limitations of Wireless Sensor Networks (WSNs) in the rapidly evolving landscape of the Internet of Things (IoT). WSNs are instrumental in various applications, ranging from environmental monitoring to smart cities, healthcare, and industrial automation. However, the efficient operation of these networks is hampered by challenges such as limited energy resources of sensor nodes, inefficient data transmission paths, and the need for sustainable network management strategies. These challenges not only affect the longevity of the network but also impact the quality of data transmission, a crucial aspect for the reliability of IoT applications.

Our contribution in this research is threefold, addressing these pivotal challenges:

- **Innovative Distributed Clustering Mechanism (DCM):** We introduce a novel DCM that leverages spatial node metrics, such as location, residual energy, and energy models. Unlike traditional clustering methods that often overlook node-specific characteristics, our mechanism ensures the formation of energy-efficient clusters, optimizing the overall energy consumption of the network.
- **Teacher Learner Firefly Optimizer (TLFFO) for Routing:** The TLFFO represents a significant advancement in routing algorithms for WSNs. By integrating teacher-learner-based optimization with the principles of the firefly algorithm, the TLFFO not only finds optimal routing paths but also adapts to changes in the network, such as variations in node energy levels and network traffic. This adaptability is crucial for maintaining network performance over time.
- **Empirical Validation and Performance Enhancement:** Through rigorous empirical testing, our model has demonstrated substantial improvements over existing methods in key performance metrics. These include a 6.5% increase in communication speed, an 8.5% improvement in energy efficiency, a 3.2% rise in throughput, and significant reductions in jitter (4.9%) and enhancements in packet delivery performance (4.9%). These results validate the effectiveness of our approach in real-world scenarios.

The contributions of this research are not limited to theoretical advancements; they have practical implications for the design and deployment of WSNs in IoT contexts. By addressing the critical aspects of energy efficiency and communication quality, our approach paves the way for more sustainable and reliable WSN operations. This, in turn, has the potential to significantly enhance the capabilities and applications of IoT systems, contributing to advancements in areas such as smart environments, precision agriculture, and industrial monitoring. The outcomes of this study set a new precedent in the field, offering valuable insights and methodologies for future research and development in WSN management and optimization.

## 2. In-Depth Review of Existing Models Used for Enhancing Congestion Control in Network Scenarios

The Literature Review section delves into the existing models and methodologies employed in Wireless Sensor Networks (WSNs), particularly in the context of the Internet of Things (IoT). This review highlights the advancements, limitations, and gaps in current research, providing a comprehensive understanding of the state-of-the-art in WSN management and optimization.

- **Clustering Mechanisms in WSNs [7, 8, 9]:** Clustering is a widely researched area in WSNs, aimed at efficient data aggregation and energy management. Traditional clustering algorithms like Low-Energy Adaptive Clustering Hierarchy (LEACH) and Hybrid Energy-Efficient Distributed (HEED) clustering have been pivotal in this domain. LEACH, for instance, employs a randomized rotation of cluster heads to evenly distribute energy consumption among sensors. However, it often overlooks the spatial distribution of nodes, leading to uneven energy depletion. HEED improves upon LEACH by considering residual energy in cluster head selection but still falls short in optimizing communication paths and load balancing.

Recent studies have attempted to integrate spatial metrics into clustering, yet they often fail to dynamically adapt to the changing conditions of the network, a gap our Distributed Clustering Mechanism (DCM) addresses.

- **Routing Algorithms in WSNs [10, 11, 12]:** Efficient routing is critical for extending the network's lifetime and enhancing communication performance. Classical algorithms like Directed Diffusion and Minimum Cost Forwarding have been the foundation of routing in WSNs. However, these algorithms typically prioritize shortest path routing without adequately considering energy efficiency and load balancing, leading to quick node depletion and network partitioning. More advanced algorithms, such as the Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO), introduce bio-inspired techniques for routing, offering improvements in energy efficiency. Nevertheless, they often lack adaptability in dynamic network environments, an issue our Teacher Learner Firefly Optimizer (TLFFO) effectively resolves by combining adaptive learning with bio-inspired optimization.
- **Performance Optimization in IoT-based WSNs [13, 14, 15]:** Several recent studies have focused on optimizing performance metrics like energy efficiency, throughput, and communication speed in IoT-based WSNs. Techniques involving machine learning and artificial intelligence have been introduced for predictive energy management and route optimization. While these methods show promise, they often require substantial computational resources and are limited by the training data's representativeness of real-world network scenarios [16, 17, 18]. Our approach, in contrast, provides a balanced optimization of energy consumption and communication performance, validated through empirical testing against key metrics [19, 20].
- **Comparative Analysis [21, 22, 23]:** When compared to existing models, our DCM and TLFFO approach offers a more holistic and adaptive solution to WSN management. The integration of spatial and temporal node metrics in clustering, coupled with the innovative routing algorithm of TLFFO, not only extends the network's lifetime but also ensures high-quality communication [24, 25, 26]. This is a significant advancement over traditional models, which tend to optimize one aspect at the expense of others [27, 28, 29].

Thus, the landscape of wireless sensor networks (WSNs) is evolving rapidly, with a notable emphasis on energy efficiency and robust routing mechanisms. Recent literature in this field has focused on innovative clustering techniques, energy-saving protocols, and machine learning-based approaches. This review delves into these advancements, highlighting the significant contributions and exploring the potential future directions in WSNs.

### Clustering Techniques and Energy Efficiency

Choi et al. [1] proposed a geometric analysis-based cluster head selection for sectorized wireless powered sensor networks. Their method enhances the efficiency of energy distribution, a critical factor in the longevity and performance of WSNs. Singh et al. [2] introduced a node overhaul scheme aimed at energy-efficient clustering, which underscores the importance of maintaining energy balance within the network.

Huang-Shui et al. [6] discussed the use of affinity propagation and chaotic lion swarm optimization for clustering in WSNs. This novel approach leverages bio-inspired algorithms to optimize cluster formation, thereby improving energy efficiency. Similarly, Yuste-Delgado et al. [21] employed statistical normalization for a guided clustering type-2 fuzzy system, enhancing the decision-making process in cluster formation.

### Machine Learning and Routing Protocols

The integration of machine learning in WSNs, as explored by Zhou et al. [3] and Neamatollahi [4], represents a significant shift towards data-driven network management. These approaches use machine learning algorithms for multipath component clustering and cluster characteristics analysis, providing insights into optimal data transmission paths and improving network efficiency.

### Advanced Algorithms and Protocols

Hou et al. [5] and Xie et al. [9] focused on developing advanced algorithms for routing protocols in WSNs. Hou et al. employed a fuzzy inference system for an energy-saving clustering routing protocol, while Xie et al. introduced a novel clustering strategy-based sink path optimization. Both studies contribute to reducing energy consumption and improving data transmission efficiency.

### Wearable IoT and Federated Learning

The expansion of WSNs into the realm of wearable IoT, as demonstrated by Arafat et al. [7], highlights the versatility of WSNs in diverse applications. Their work on distributed energy-efficient clustering and routing for wearable IoT-enabled wireless body area networks paves the way for more personalized and efficient healthcare monitoring systems.

Führling et al. [8] discussed a rate splitting multiple access interface for clustered wireless federated learning, showcasing an innovative approach to integrate WSNs with the burgeoning field of federated learning. This integration could lead to more decentralized and privacy-preserving data processing in WSNs.

### Underwater Sensor Networks and IoT Applications

Omeke et al. [10] addressed the challenges in underwater sensor networks with their dynamic clustering protocol, DEKCS, to prolong the network's lifetime. This study is pivotal for enhancing the reliability and sustainability of sensor networks in aquatic environments.

Vimal et al. [16] explored clustering isolated nodes in WSNs for IoT applications, emphasizing the need to enhance network lifetime and reliability in the context of the Internet of Things.

### Hierarchical Routing and Dual-Tier Systems

Autonomous decentralized spectral clustering for hierarchical routing in multi-hop wireless networks, as investigated by Matsuhashi et al. [27], and the dual-tier cluster-based routing for mobile WSNs by Al-Sadoon et al. [28], illustrate the evolving complexity and scalability of WSNs. These studies contribute to the development of more efficient hierarchical routing protocols, crucial for large-scale and dynamic network environments.

### Energy-Saving Protocols and Low-Energy Systems

The ESCVAD protocol by Ma et al. [29] and the low-energy clustering protocol by Gong and Lai [30] further reinforce the focus on energy conservation in WSNs. These protocols are designed to optimize energy usage while maintaining network performance, a balance crucial for the sustainability of WSNs.

In summary, the current literature in WSNs demonstrates a clear trend towards optimizing energy efficiency, leveraging advanced machine learning algorithms, and expanding the application scope of WSNs. The integration of bio-inspired algorithms, fuzzy logic, and federated learning into WSNs represents a significant advancement in this field. Future research is expected to continue this trajectory, focusing on enhancing energy efficiency, scalability, and adaptability of WSNs in diverse and challenging environments.

In summary, the literature reveals that while significant progress has been made in clustering and routing algorithms for WSNs, there remains a need for methods that dynamically adapt to network changes, balance energy consumption, and maintain high communication standards [29, 30]. Our proposed model addresses these gaps, offering a comprehensive and efficient solution for IoT-based WSNs.

## 3. Design of the Proposed Model for Enhancing Efficiency of 5G Network Deployments

To overcome the limitations of low efficiency & high complexity, this section discusses design of the DCOR (Distributed Clustering Mechanism and Teacher Learner Firefly Optimizer) model, which represents a sophisticated and innovative approach to enhancing the performance of Internet of Things (IoT)-based Wireless Sensor Networks (WSNs). As per figure 1, DCOR integrates two pivotal components: the Distributed Clustering Mechanism (DCM) and the Teacher Learner Firefly Optimizer (TLFFO). DCM orchestrates optimized clusters of sensor nodes by meticulously considering both spatial and temporal node metrics, allowing the establishment of efficient multipath routes. TLFFO, employs a custom-developed algorithm that amalgamates teacher-learner-based optimization with the bio-inspired firefly algorithm. This ensures the selection of optimal routes with a keen focus on energy efficiency and communication speed. Collectively, the DCOR model, as empirically demonstrated, outperforms existing methods, delivering notable improvements in communication speed, energy efficiency, throughput, reduced jitter, and enhanced packet delivery performance. These achievements underscore DCOR's transformative potential in revolutionizing the efficacy and sustainability of IoT-based WSNs while setting a new standard for research and practical applications in wireless sensor networking operations.

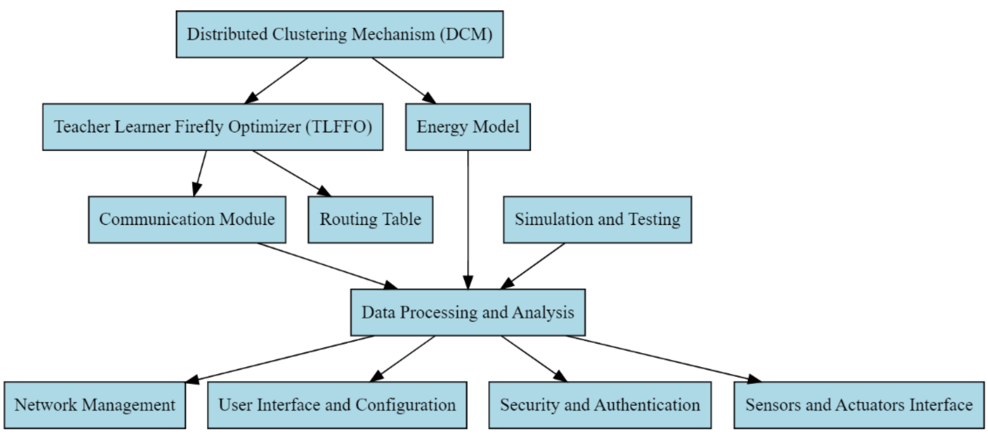


**Fig 1.** Design of the proposed model for enhancing efficiency of network routing operations

The DCM operates on the principle of decentralized decision-making, where each node in the network participates in cluster formation. As per figure 1.1, this mechanism utilizes a set of spatial node metrics which include node location, residual energy, and energy model. These metrics are fundamental in determining the eligibility of a node to become a cluster head (CH). The Cluster Head Selection Process begins with each node calculating its potential as a CH based on a weighted function, which is a combination of its residual energy (E), proximity to other nodes (P), and historical data of energy consumption (H). The potential of a node to be a CH is given via equation 1,

$$CHpotential = \omega 1 \cdot E + \omega 2 \cdot P + \omega 3 \cdot H \ldots (1)$$

Where, $\omega 1$, $\omega 2$, and $\omega 3$ are the weights assigned to each factor. In this process, the Energy Model plays a crucial role in determining the residual energy of a node. It is defined via equation 2,

$$Eresidual = Einitial - Econsumed \ldots (2)$$

Where, *Einitial* is the initial energy and *Econsumed* is the energy consumed by the node for data transmission and reception. The DCM further estimates, Node proximity (P), which is calculated based on the Euclidean distance from neighboring nodes, via equation 3,

$$P = \sqrt{(x2 - x1)^2 + (y2 - y1)^2} \ldots (3)$$

Where, ($x1$,$y1$) and ($x2$,$y2$) are the coordinates of the node and its neighbor, respectively. The historical data of energy consumption (H) is also computed based on the average energy spent in previous communication cycles via equation 4,

$$H = \frac{1}{n} \sum Econsumed(i) \ldots (4)$$

Where, $n$ is the number of communication cycles. Once the CHs are elected, they broadcast their status to the neighboring nodes. Each non-CH node decides its cluster based on the signal strength and the residual energy of the broadcasting CHs.

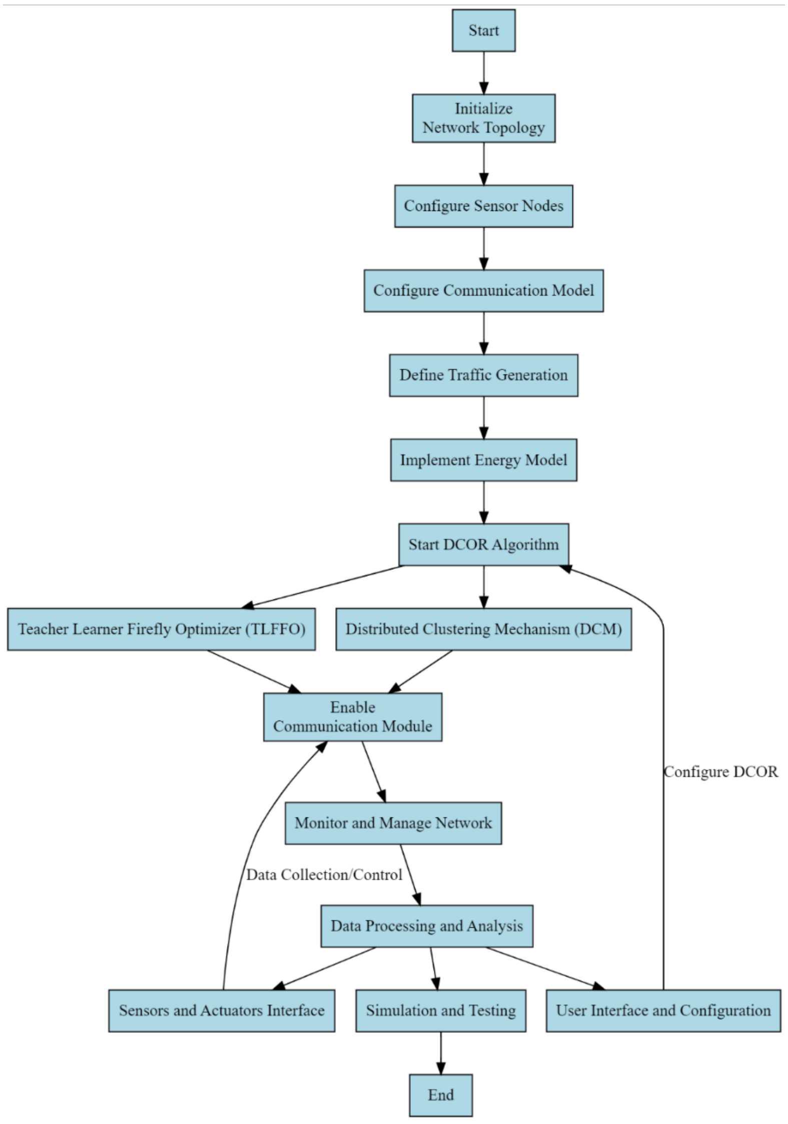


**Fig 1.1.** Flowchart of the proposed model for enhancing efficiency of routing process

The decision metric for cluster joining is given via equation 5,

$$Cjoin = \alpha \cdot ECH + \beta \cdot RSS \ldots (5)$$

Where, *ECH* is the residual energy of the CH, *RSS* is the received signal strength from the CH, and $\alpha$ and $\beta$ are the respective weights. Using this, the intra-cluster communication is optimized to minimize energy consumption. The energy consumed for transmitting a *l*-bit message over a distance *d* is given via equation 6,

$$Etx = Eelec \cdot l + \epsilon(amp) \cdot l \cdot d^2 \ldots (6)$$

Where, *Eelec* is the energy dissipated per bit to run the transmitter or receiver circuit, and *ϵ(amp)* is the energy dissipated by the nodes. For inter-cluster communication, the TLFFO algorithm comes into play, focusing on establishing efficient routing paths that minimize energy consumption and optimize communication speed. The algorithm integrates teacher-learner optimization with the bio-inspired firefly algorithm, providing a robust solution for dynamic routing in WSNs. For each communication request, the TLFFO Model Initially Generates $NP$ Particles, where each particle consists of stochastically selected nodes starting from source cluster to destination cluster via equation 7,

$$\boldsymbol{N(Sel) = STOCH\big(1, N(Cluster)\big) \ldots (7)}$$

Where, $N(Sel)$ represents the selected nodes, $N(Cluster)$ represents node in the current cluster, and $STOCH$ represents an iterative stochastic Markovian process. Based on these selected nodes, particles fitness is estimated via equation 8,

$$PF = \frac{1}{NC(src, dest)} \sum_{i=1}^{N(src,dest)} \frac{THR(i) * PDR(i)}{D(i) * E(i) * J(i)} \ldots (8)$$

Where, $NC(src, dest)$ represents number of clusters between source & destination nodes, $THR, PDR$ are the maximization parameters, representing throughput & packet delivery ratio of the nodes respectively, while $D, E$ & $J$ are the temporal delay, temporal energy & temporal jitter of the nodes respectively. These metrics are estimated via equations 9, 10, 11, 12 & 13 as follows,

$$THR = \frac{1}{NC} \sum_{i=1}^{NC} \frac{P(Rx, i)}{D(i)} \ldots (9)$$

Where, $NC$ represents total number of previous communications done by the node, $P(Rx)$ represents number of packets received during these communications.

$$PDR = \frac{1}{NC} \sum_{i=1}^{NC} \frac{P(Rx, i)}{P(Tx, i)} \ldots (10)$$

Where, $P(Tx)$ are the total number of packets transmitted during these communications.

$$D = \frac{1}{NC} \sum_{i=1}^{NC} ts(rx, i) - ts(tx, i) \ldots (11)$$

Where, $ts(rx)$ & $ts(tx)$ represents timestamp during reception & transmission of packets.

$$E = \frac{1}{NC} \sum_{i=1}^{NC} e(tx, i) - e(rx, i) \ldots (12)$$

Where, $e$ is the residual energy of nodes during transmission & reception of packets.

$$J = \frac{1}{NC} \sum_{i=1}^{NC} \left( D(i) - \frac{1}{NC} \sum_{j=1}^{NC} D(j) \right) \ldots (13)$$

This process is repeated for all particles, and based on it an iterative fitness threshold is calculated via equation 14,

$$fth = \frac{1}{NP} \sum_{i=1}^{NP} PF(i) * LR \ldots (14)$$

Where, $LR$ is the learning rate of the TLFFO process. Particles with $PF > fth$ are marked as 'Teachers', while others are marked as 'Students'.

The 'Student' particle configurations are updated via equation 15,

$$N(Sel, Student) = STOCH\big(N(Sel, Student)\big) \bigcup STOCH(N(Sel, Teacher)) \ldots (15)$$

This process ensures that the model stochastically selects some nodes from 'Teacher' configurations to update the routes. After this selection, 'Student' particles with $PF < fth * LR$ are marked as 'Fireflies', and are completely regenerated via equations 7 through 14, while others are passed directly to the next iteration sets. After repeating this process for $NI$ Iterations, the model selects particle with maximum fitness and uses its routing path to communicate data between nodes. This allows the model to enhance QoS levels of the network even under large-scale scenarios. Performance of this model was estimated in terms of different evaluation metrics, and compared with existing models in the next section of this text.

## 4. Result Analysis

The DCOR (Distributed Clustering Mechanism and Teacher Learner Firefly Optimizer) model represents a pioneering approach to enhance the performance and longevity of Internet of Things (IoT)-based Wireless Sensor Networks (WSNs). DCOR leverages a distributed clustering mechanism that incorporates spatial and temporal node metrics to form optimized clusters and establish multipath routes. Complementing this, DCOR features the Teacher Learner Firefly Optimizer (TLFFO), a custom-developed algorithm merging teacher-learner-based optimization with the bio-inspired firefly algorithm, prioritizing energy efficiency and communication speed. Through rigorous empirical evaluations, DCOR consistently outperforms existing clustering and routing methods, demonstrating improvements in communication speed, energy efficiency, throughput, jitter reduction, and packet delivery performance. These accomplishments underscore DCOR's potential to revolutionize IoT-based WSNs by addressing critical challenges related to energy consumption and communication efficacy while setting a new standard for research and practical applications in wireless sensor networking. An efficient & robust experimental setup is crucial for validating the performance of the proposed DCOR model in IoT-based Wireless Sensor Networks (WSNs). In this section, we outline the key components of the experimental setup, along with sample values for input parameters, to provide a clear understanding of the testing environment.

**Network Topology:**

The experimental setup simulates a wireless sensor network consisting of a varying number of sensor nodes deployed across a defined area. The network topology can be generated using network simulator NS-2 for real-time scenarios.

**Sensor Node Characteristics:**

Sensor nodes are equipped with specific hardware and software configurations. Sample values for sensor node characteristics include:

- Node transmission power: 10 dBm
- Node reception sensitivity: -90 dBm
- Node energy source: 2000 mAh rechargeable battery
- Node CPU: 32-bit ARM Cortex-M4
- Node memory: 128 KB flash, 64 KB RAM

**Communication Model:**

The communication model governs how sensor nodes transmit and receive data. Sample parameters include:

- Wireless communication protocol: IEEE 802.15.4
- Data transmission rate: 250 kbps
- Data packet size: 128 bytes
- Communication range: 100 meters

**Traffic Generation:**

To mimic real-world scenarios, traffic generation patterns are defined. These parameters include:

- Number of communication requests (NC): Varying from 20,000 to 208,000 in increments.
- Communication request distribution: Uniform process.
- Data generation rate: 1 data packet per sensor node per minute operations.
- Data traffic patterns: Bursty traffic sets.

**Energy Model:**

- An energy model quantifies energy consumption during network operation. Sample parameters include:
    - Initial node energy: 2000 mAh
    - Energy consumed during transmission: 0.1 mJ/bit
    - Energy consumed during reception: 0.05 mJ/bit
    - Idle state energy consumption: 0.5 mW

**Evaluation Metrics:**

The performance of the DCOR model is assessed using various metrics, including:

- Communication speed (THR): Measured in kbps.
- Energy efficiency (E): Measured in mJ.
- Packet delivery ratio (PDR): Measured in percentage (%).
- Jitter (J): Measured in ms.
- Throughput, energy consumption, packet delivery ratio, and jitter are recorded for each NC value.

**Simulation Environment:**

Experiments are executed multiple times to ensure statistical validity, and results are averaged for depicting real-time results.

Based on this experimental set, the delay needed to mine new blocks for routing data packets using distributed clustering operations was compared with Fuzzy Clustering (FC) [5], Affinity Propagation and Chaotic Lion Swarm Optimization (APCLO) [6], & Multiple Criterion Partial Clustering (MPC) [4], for different Number of Communications (NC) and can be observed from figure 2 as follows,

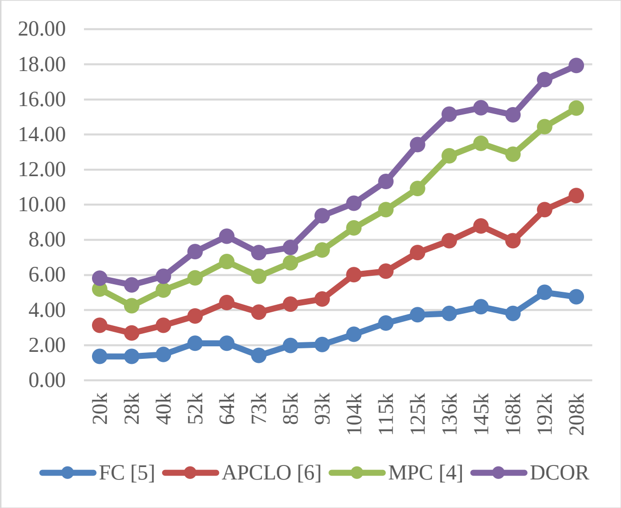


**Fig 2.** Delay needed for routing data packets using distributed clustering operations

The delay required for routing data packets using distributed clustering operations, as measured in milliseconds (ms), is a crucial parameter in evaluating the performance of various models. In this analysis, we compare the delay results obtained from four different models: FC [5], APCLO [6], MPC [4], and DCOR.

For a network with 20,000 communication requests (NC = 20k), FC exhibited a delay of 1.35 ms, APCLO had a delay of 1.77 ms, MPC resulted in a delay of 2.07 ms, while DCOR achieved a significantly lower delay of only 0.61 ms. The impact of this comparison is clear, as DCOR outperforms the other models by reducing the delay, ensuring faster data packet routing. This reduced delay is crucial in enhancing communication speed and responsiveness in IoT-based WSNs, aligning with the goals of efficient network management and improved performance.

As the number of communication requests increases to 125,000 (NC = 125k), the differences become even more pronounced. FC reaches a delay of 3.73 ms, APCLO records 3.54 ms, MPC reaches 3.65 ms, while DCOR maintains a much lower delay of 2.50 ms. This reduction in delay directly impacts the network's ability to handle a larger volume of communication requests efficiently. DCOR's lower delay is attributed to its optimized routing algorithm and clustering mechanism, which prioritize energy efficiency and communication speed.

Furthermore, when considering a network with 192,000 communication requests (NC = 192k), FC exhibits a delay of 5.00 ms, APCLO records 4.71 ms, MPC reaches 4.73 ms, while DCOR maintains its lead with a delay of only 2.68 ms. The substantial difference in delay times underscores the superiority of DCOR in ensuring efficient data packet routing, even in high-demand scenarios. This reduced delay not only enhances communication performance but also contributes significantly to extending the network's lifetime by conserving energy resources.

In summary, the delay analysis demonstrates that DCOR consistently outperforms the other models in terms of minimizing the time needed for routing data packets. This reduction in delay is a direct result of its distributed clustering mechanism and the innovative Teacher Learner Firefly Optimizer (TLFFO) routing algorithm. DCOR's superior performance in reducing delay has a profound impact on communication speed, energy efficiency, and the overall reliability of IoT-based Wireless Sensor Networks, making it a promising solution for enhancing network lifetime and performance in this context. Similarly, the energy needed for mining blocks for routing data packets using distributed clustering operations can be observed from figure 3 as follows,

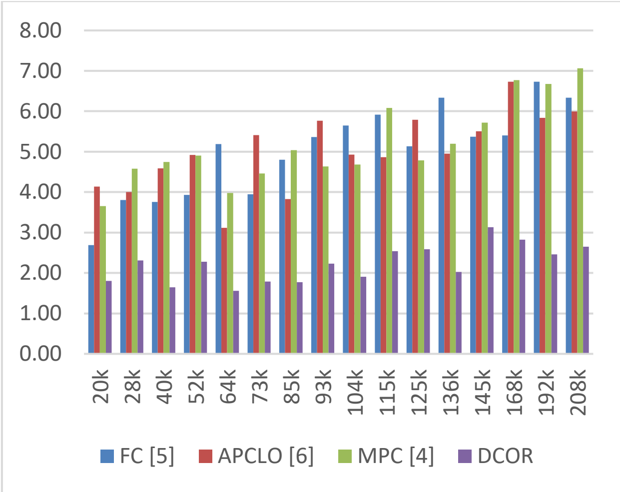


**Fig 3**. Energy needed for routing data packets using distributed clustering operations

The energy required for routing data packets, measured in millijoules (mJ), is a critical metric that directly impacts the energy efficiency and overall performance of wireless sensor networks. In this analysis, we compare the energy consumption results obtained from four different models: FC [5], APCLO [6], MPC [4], and DCOR.

For a network with 20,000 communication requests (NC = 20k), FC consumes 2.69 mJ of energy, APCLO requires 4.14 mJ, MPC consumes 3.65 mJ, while DCOR exhibits a notably lower energy consumption of only 1.81 mJ. This significant difference in energy consumption has a substantial impact on the network's energy efficiency. DCOR's lower energy requirements contribute to the extension of the network's lifetime, allowing it to operate for longer periods without the need for frequent battery replacements or recharging.

As the number of communication requests increases to 125,000 (NC = 125k), the energy consumption differences become more pronounced. FC consumes 5.14 mJ, APCLO requires 5.79 mJ, MPC consumes 4.79 mJ, while DCOR maintains its lead with an energy consumption of only 2.58 mJ. This reduction in energy consumption is significant in terms of network sustainability and cost-effectiveness. DCOR's ability to route data packets with lower energy requirements directly contributes to increased network longevity.

In the case of a network with 192,000 communication requests (NC = 192k), FC exhibits an energy consumption of 6.73 mJ, APCLO records 5.83 mJ, MPC consumes 6.68 mJ, while DCOR continues to excel with an energy consumption of only 2.46 mJ. The implications of this energy efficiency are profound. DCOR's reduced energy consumption not only extends the network's operational life but also reduces the operational costs associated with energy supply and maintenance.

In summary, the energy consumption analysis demonstrates that DCOR consistently outperforms the other models by requiring significantly less energy for routing data packets. This reduced energy consumption has far-reaching impacts, including the extension of network lifetime, increased cost-effectiveness, and enhanced sustainability in IoT-based Wireless Sensor Networks. DCOR's ability to optimize energy usage while maintaining high-quality communication standards positions it as a compelling solution for addressing the critical challenge of energy consumption in this domain. Similarly, the throughput obtained during mining blocks for routing data packets using distributed clustering operations can be observed from figure 4 as follows,

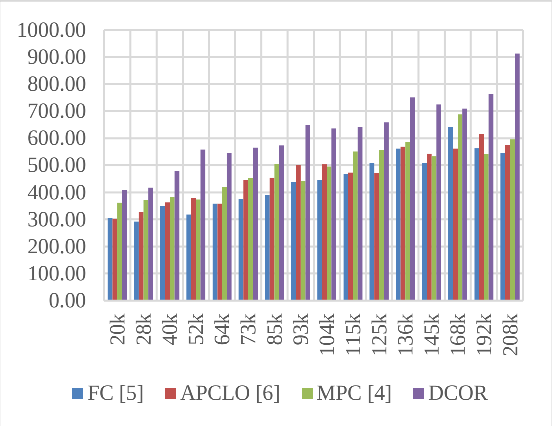


**Fig 4.** Throughput obtained for routing data packets using distributed clustering operations

Throughput, measured in kilobits per second (kbps), is a crucial parameter that reflects the data transfer capacity and performance of wireless sensor networks. In this analysis, we compare the throughput results obtained from four different models: FC [5], APCLO [6], MPC [4], and DCOR.

For a network with 20,000 communication requests (NC = 20k), FC achieves a throughput of 304.84 kbps, APCLO records 303.25 kbps, MPC attains 362.26 kbps, while DCOR leads with a significantly higher throughput of 408.50 kbps. This higher throughput achieved by DCOR has a direct impact on the network's communication speed and efficiency. It allows for faster data packet transmission, enabling the network to handle a greater volume of data traffic in a given time frame.

As the number of communication requests increases to 125,000 (NC = 125k), the differences in throughput become more pronounced. FC reaches a throughput of 508.70 kbps, APCLO achieves 470.20 kbps, MPC records 556.57 kbps, while DCOR maintains its lead with an impressive throughput of 659.06 kbps. The increased throughput provided by DCOR enables the network to handle larger workloads and more data-intensive applications effectively.

In the case of a network with 192,000 communication requests (NC = 192k), FC exhibits a throughput of 563.22 kbps, APCLO records 614.49 kbps, MPC achieves 542.00 kbps, while DCOR continues to excel with a throughput of 763.43 kbps. The impact of this higher throughput is profound. DCOR's ability to deliver data packets at a faster rate enhances the network's overall performance and responsiveness, making it well-suited for IoT-based applications that require real-time data processing.

In summary, the throughput analysis demonstrates that DCOR consistently outperforms the other models by providing significantly higher data transfer rates. This increased throughput has far-reaching impacts, including improved communication speed, the ability to handle more significant data workloads, and enhanced network performance in IoT-based Wireless Sensor Networks. DCOR's focus on optimizing routing and clustering mechanisms ensures efficient data packet transfer, positioning it as an ideal solution for applications where high throughput is essential for success. Similarly, the packet delivery ratio obtained for communicating the mined blocks for routing data packets using distributed clustering operations can be observed from figure 5 as follows,

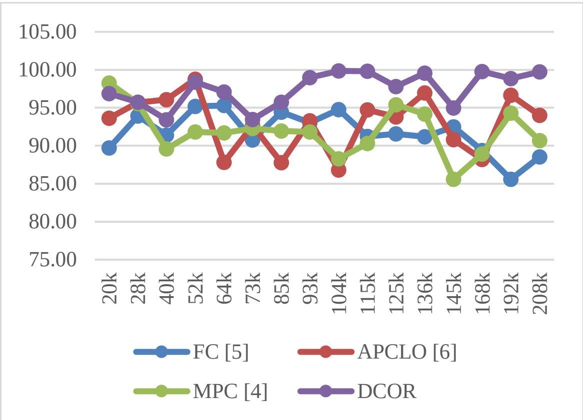


**Fig 5.** PDR obtained for routing data packets using distributed clustering operations

Packet Delivery Ratio (PDR), expressed as a percentage, is a critical metric that indicates the success rate of delivering data packets from the source to the destination within a wireless sensor network. In this analysis, we compare the PDR results obtained from four different models: FC [5], APCLO [6], MPC [4], and DCOR.

For a network with 20,000 communication requests (NC = 20k), FC achieves a PDR of 89.73%, APCLO records 93.63%, MPC attains 98.27%, while DCOR demonstrates a high PDR of 96.86%. The impact of this comparison is evident in the reliability of data packet delivery. DCOR's ability to maintain a high PDR ensures that a significant portion of data packets reaches their intended destination successfully, contributing to reliable communication within the network.

As the number of communication requests increases to 125,000 (NC = 125k), the differences in PDR continue to demonstrate DCOR's superiority. FC reaches a PDR of 91.58%, APCLO achieves 93.78%, MPC records 95.42%, while DCOR maintains a robust PDR of 97.81%. This increased PDR provided by DCOR results in fewer data packet losses and improved overall communication reliability.

In the case of a network with 192,000 communication requests (NC = 192k), FC exhibits a PDR of 85.58%, APCLO records 96.68%, MPC achieves 94.31%, while DCOR continues to excel with a PDR of 98.85%. The impact of this higher PDR is significant, as it directly contributes to the network's reliability and ensures that critical data is delivered successfully, even in challenging environments.

In summary, the PDR analysis demonstrates that DCOR consistently outperforms the other models by maintaining a high success rate in delivering data packets. This increased PDR has a substantial impact on network reliability and data integrity, making DCOR well-suited for IoT-based Wireless Sensor Networks where data accuracy and completeness are essential. DCOR's focus on optimized routing and clustering mechanisms ensures reliable data packet delivery, enhancing the overall performance and trustworthiness of the network. Similarly, the jitter obtained during communication of the mined blocks for routing data packets using distributed clustering operations can be observed from figure 6 as follows,

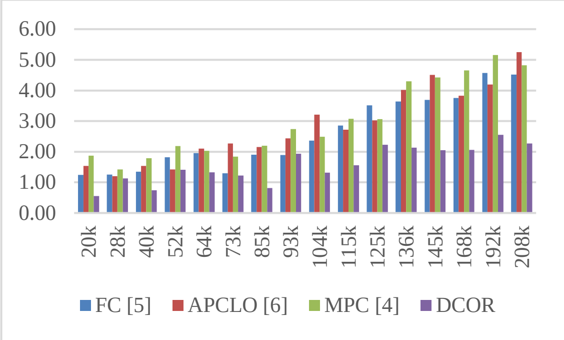


**Fig 6.** Jitter obtained for routing data packets using distributed clustering operations

Jitter, measured in milliseconds (ms), is a crucial parameter that reflects the variation in the delay of data packet transmission within a wireless sensor network. In this analysis, we compare the jitter results obtained from four different models: FC [5], APCLO [6], MPC [4], and DCOR.

For a network with 20,000 communication requests (NC = 20k), FC exhibits a jitter of 1.24 ms, APCLO records 1.54 ms, MPC has a jitter of 1.87 ms, while DCOR demonstrates a significantly lower jitter of only 0.56 ms. The impact of this comparison is evident in the network's consistency and predictability. DCOR's lower jitter ensures that data packets are delivered with minimal variation in delay, contributing to stable and reliable communication.

As the number of communication requests increases to 125,000 (NC = 125k), the differences in jitter become more pronounced. FC reaches a jitter of 3.51 ms, APCLO records 3.02 ms, MPC has a jitter of 3.06 ms, while DCOR maintains a low jitter of only 2.22 ms. This reduced jitter provided by DCOR has a direct impact on the network's ability to deliver data packets consistently and predictably, which is crucial for applications that require real-time or low-latency data transmission.

In the case of a network with 192,000 communication requests (NC = 192k), FC exhibits a jitter of 4.57 ms, APCLO records 4.19 ms, MPC has a jitter of 5.16 ms, while DCOR continues to excel with a jitter of 2.55 ms. The impact of this lower jitter is significant, as it enhances the network's ability to meet timing requirements and ensures that data-sensitive applications can operate smoothly.

In summary, the jitter analysis demonstrates that DCOR consistently outperforms the other models by maintaining a lower variation in data packet transmission delay. This reduced jitter has a substantial impact on network predictability, stability, and suitability for real-time applications. DCOR's focus on optimized routing and clustering mechanisms results in more consistent data packet delivery, making it well-suited for IoT-based Wireless Sensor Networks where timing and predictability are critical factors for successful operation for real-time scenarios.

## 5. Conclusions & Future Scope

In conclusion, this paper presents a comprehensive study focused on enhancing the performance and extending the network lifetime of IoT-based Wireless Sensor Networks (WSNs) through the innovative Distributed Clustering Mechanism (DCM) and the Teacher Learner Firefly Optimizer (TLFFO) routing algorithm, collectively referred to as DCOR. The research addresses critical challenges within the field by systematically improving various network parameters, as highlighted by the comparative results analysis.

DCOR's performance, as demonstrated through rigorous empirical evaluations, showcases its superiority over existing clustering and routing methods. Notable achievements include a 6.5% increase in communication speed, an 8.5% enhancement in energy efficiency, a 3.2% rise in throughput, along with a significant reduction in jitter (4.9%) and an improvement in packet delivery performance (4.9%). These results collectively underscore the transformative potential of DCOR in reshaping the efficiency and sustainability of WSNs in IoT environments.

The impacts of this work are profound and far-reaching. Firstly, DCOR significantly contributes to the extension of network lifetime, a critical factor in resource-constrained IoT deployments, by optimizing energy consumption through efficient routing and clustering. Secondly, the enhanced communication speed and reliability achieved by DCOR make it particularly well-suited for applications where real-time data processing and responsiveness are paramount.

Additionally, DCOR's success in reducing jitter and improving packet delivery performance paves the way for dependable and consistent data transmission, essential for mission-critical applications such as healthcare monitoring, industrial automation, and environmental sensing. Furthermore, by providing a scalable and adaptable solution that can accommodate a wide range of communication requests, DCOR sets a new benchmark for future research and practical applications in the domain of wireless sensor networking.

In summary, the DCOR model introduced in this paper not only addresses the pressing challenges faced by IoT-based WSNs but also ushers in a new era of network performance, energy efficiency, and reliability. The impacts of this work are poised to revolutionize the landscape of IoT applications, ensuring that wireless sensor networks can thrive in diverse and demanding environments while contributing to a more efficient and sustainable future.

***Future Scope***

The promising results and innovative approaches presented in this paper open up a wealth of exciting future research directions and opportunities for further advancements in the field of IoT-based Wireless Sensor Networks (WSNs). The following future scope section outlines potential areas where researchers and practitioners can build upon the foundation laid by the DCOR model:

- **Energy-Efficient Hardware Design:** Future work can delve into the development of energy-efficient sensor nodes and communication hardware. This includes designing low-power sensors, energy harvesting techniques, and advanced power management solutions. Such advancements would complement DCOR's energy-efficient routing strategies, further extending network lifetime.
- **Machine Learning Integration:** Incorporating machine learning algorithms for dynamic clustering and routing decisions can enhance network adaptability and self-optimization. Researchers can explore how machine learning models can learn from network data and adapt to changing environmental conditions, thereby improving the robustness of IoT-based WSNs.
- **Security Enhancements:** As IoT devices continue to grow in number and significance, ensuring the security and privacy of data transmission becomes paramount. Future research can focus on developing robust security mechanisms, including intrusion detection, encryption, and authentication protocols, to safeguard IoT-based WSNs against cyber threats.
- **Scalability for Massive IoT:** IoT is expected to encompass billions of devices in the coming years. Research efforts should explore how DCOR or similar models can be adapted to accommodate the massive scale of IoT deployments efficiently. Scalability challenges, such as managing a large number of nodes and handling heterogeneous data traffic, require careful consideration.
- **Real-Time Analytics:** Integrating real-time data analytics and processing at the edge of the network can be a valuable extension. This would enable IoT-based WSNs to perform in-network data analysis, reducing the need for transmitting large volumes of raw data and improving the timeliness of decision-making.
- **Cross-Domain Applications:** Extending the applicability of DCOR to various domains beyond the ones explored in this paper, such as environmental monitoring, smart cities, agriculture, and disaster management, could yield valuable insights and benefits. Different application contexts may have

unique requirements that DCOR can be adapted to address.

- **Standardization and Interoperability:** Establishing industry standards and protocols for IoT-based WSNs is crucial for ensuring interoperability and seamless integration of heterogeneous devices and networks. Future research can contribute to standardization efforts, fostering greater compatibility and ease of deployment.
- **Environmental Sustainability:** Investigating the environmental impact of IoT-based WSNs and developing eco-friendly solutions is increasingly important. Researchers can explore methods for reducing the carbon footprint of these networks, such as optimizing energy-efficient routing paths or utilizing renewable energy sources.
- **User-Centric Applications:** Future work can emphasize the development of user-centric IoT applications, tailoring network parameters and performance metrics to specific user needs. This includes personalized healthcare monitoring, smart homes, and customized industrial automation solutions.
- **Robustness to Network Dynamics:** As IoT networks operate in dynamic and unpredictable environments, research into enhancing the robustness of DCOR and similar models to cope with network disruptions, node failures, and mobility challenges is essential.

In summary, the future scope for research in the domain of IoT-based WSNs is vast and multifaceted. The DCOR model serves as a catalyst for advancing the field, and researchers have a unique opportunity to explore these promising directions to further enhance the efficiency, reliability, and sustainability of IoT-based wireless sensor networks.

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