

An Intelligent Approach for Radio Access Technology Selection in Heterogeneous Routing Multi-Service IoT Based Wireless Networks

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ABSTRACT

There has been a dramatic shift in data-driven applications due to the proliferation of the IoT and WSNs, which have made possible intelligent infrastructure management, environmental sensing, and real-time monitoring [1, 2]. Keeping the network running efficiently while ensuring dependable data delivery with low latency is essential for these applications. Nevertheless, maintaining the durability and performance of the network is greatly hindered by the restricted resources of the sensor nodes, such as their low processing power and battery capacity. Especially in large-scale and diverse WSN settings, it is vital to provide optimal routing algorithms in order to balance energy usage and minimise communication delay [3, 4]. Preliminary results from simulation-based performance assessments show that the ELBPFO method outperforms state-of-the-art clustering-based routing methods in terms of energy consumption, network stability, latency reduction, and hotspot issue reduction. To help promote energy-efficient and low-latency communication networks, the suggested architecture offers a scalable and flexible solution for real-world IoT-WSN installations.

Keywords: WSN, IoT, Routing, Clustering, Cluster Head.

1 Introduction

One promising approach to improving network scalability and optimising energy use is clustering-based routing, which groups sensor nodes into clusters [5, 6]. By minimising duplicate communication and extending the lifetime of the network, the cluster head (CH) takes on the role of data aggregation and transmission [7], [8]. However, prior research has shown that traditional clustering methods might cause an unequal drain on CH energy, especially for nodes close to the sink node, which can hasten the network's demise [9], [10]. Furthermore, the majority of current clustering algorithms only optimise for one goal at a time, ignoring the important trade-offs between energy efficiency, communication latency, and network stability [11], [12].

This research presents the ELBPFO architecture for time-driven Internet of Things (IoT) application provisioning in WSNs as a solution to these problems. Key performance parameters like residual energy, node centrality, transmission distance, packet failure probability, and network load distribution are taken into account by the proposed approach's multi-objective optimisation process. By dynamically assigning adaptive weights to these factors depending on real-time network circumstances, ELBPFO ensures optimum CH selection and fair load balancing, unlike previous clustering approaches [12], [13]. To top it all off, this research makes use of an energy-efficient routing optimisation method that improves the efficiency of end-to-end data transmission by reducing both energy usage and latency. The suggested architecture assures dependable data transmission, decreases packet loss, and greatly enhances network lifespan by using a multi-objective decision-making paradigm.

2 Literature Survey

By guaranteeing the collection, processing, and transmission of data in real-time, Wireless Sensor Networks

(WSNs) are vital in providing event-driven Internet of Things (IoT) applications. On the other hand, WSNs' efficiency and dependability are severely impacted by energy limitations, packet losses, and load imbalance. To improve the performance of IoT applications, this literature review examines new developments in WSN failure optimisation, energy-aware routing, and load balancing.

One of the primary difficulties with WSNs is energy-efficient routing. Novel methods to reduce power consumption and increase network lifespan have been suggested in a number of research papers. Through the use of a new Memetic Algorithm, Zhang et al. [4] provide an adaptive clustering routing protocol that optimises energy efficiency by altering cluster heads and transmission pathways dynamically. When it comes to energy-efficient routing, Gangal et al. [5] suggest Distributed LEACH-AHP, which combines Analytical Hierarchy Process (AHP) with LEACH clustering. Scalability and flexibility are both improved by the distributed method. To enhance energy efficiency and decrease communication overhead in large-scale WSNs, Meenakshi et al. [6] introduce the Engroove LEACH clustering protocol, which combines LEACH with ANTfly optimisation. To improve energy saving while dealing with inadequate load balancing, Shahid et al. [7] provide an energy-efficient routing protocol that optimises route selection using connection quality measures.

Overall network lifespan is reduced due to fast energy depletion in certain nodes caused by load imbalance. Several distributed and hierarchical methods tackle this problem. In order to guarantee end-to-end dependability in WSNs that use many hops and connections, Ma et al. [8] devised a Hierarchical Traffic Offloading Mechanism. By intelligently spreading workloads among static nodes, Blessina Preethi and Nair's [9] hybrid KGNN-AHP strategy enhances energy sustainability in heterogeneous WSNs. While Chithaluru et al. [10] offer a lightweight energy-efficient routing scheme optimised for real-time WSN-VANET applications, they fail to address the need for time-driven IoT applications because they do not minimise packet failures. Instead, they focus on optimising node utilisation to mitigate load imbalance.

Data integrity and network performance are affected when packet failures occur as a result of congestion, interference, or poor transmission channels. For energy-harvesting WSNs, Mortada et al. [11] provide a Location Information-Based Routing Protocol that boosts cognitive radio network dependability and packet delivery rates. For large-scale WSNs with dense nodes, Gantassi et al. [12] suggest using the IR-DV-Hop localisation method in conjunction with a Mobile Data Collector (MDC) to improve network quality of service and decrease packet loss. To reduce the occurrence of packet loss in WSNs powered by the Internet of Things (IoT), Vankdothu et al. [13] create an interference and congestion secure routing protocol with adaptive congestion management features.

Recent research on WSNs has shown promising developments in energy-aware routing, load balancing, and optimising for packet failures. In order to improve the scalability, energy efficiency, and real-time flexibility of time-driven Internet of Things applications—which are crucial for dependable data transmission and efficient network operation—future studies should include heuristic models with multi-objective optimisation methods.

3 Problem Statement

Constructing wireless sensor networks (WSN) for IoT applications is fraught with difficulty due to the specific problems and obstacles that must be overcome. The goal of these networks is to provide first-rate service for a wide range of essential applications. The key to a long-lasting WSN and reliable operations in the Internet of Things is reducing the power consumption of sensors while they're running.

Traditional distributed architectures in the Internet of Things (IoT) environment have nodes fail quickly due to the high energy consumption of sending sensed data to a base station (BS). In order to lessen transmissions, the clustering method is often used. But there are a lot of problems with clustering in the Internet of Things setting, and we need answers.

If we want efficient performance in many areas, such load balancing, longer network longevity, and sustaining Quality of Service (QoS), we must solve the problems we've already mentioned. A fixed number of cluster-heads are known to each node. The demand for effective methods to choose cluster-heads according to

application requirements arises as a result. In the realm of IoT-enabled WSNs, it is really a very challenging challenge to use current state-of-the-art methods to provide suitable answers.

4 Proposed Methodology:

In order to satisfy the quality standards of time-driven Internet of Things (IoT) applications, this research introduces ELBPFO approach, which aims to improve energy efficiency and reduce communication delays. Uneven clustering, a technique for selecting cluster heads, and a model for optimising routing are the further components of the suggested strategy after an energy model. At last, we present the ELBPFO algorithm and describe its inner workings. As seen in Figure 1, WSNs are designed to serve IoT applications.

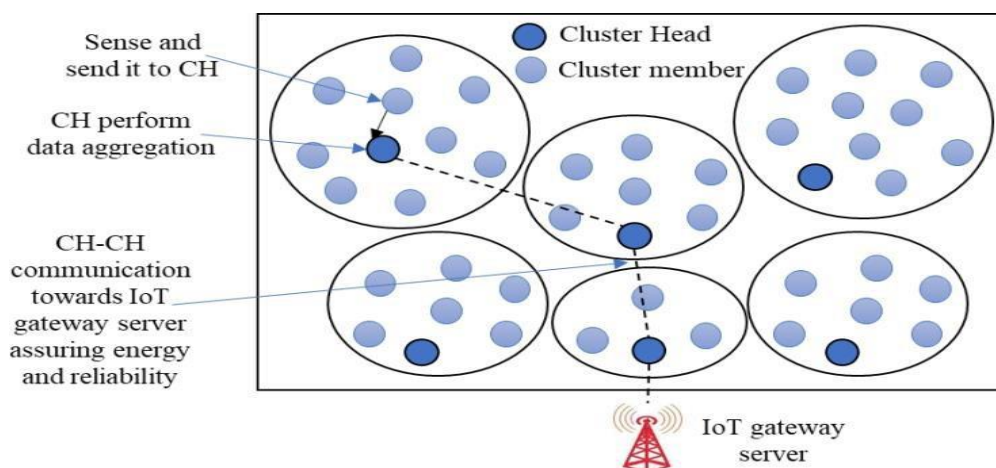


Fig-1. Unequal Cluster-based Routing Architecture using WSNs for provisioning IoT applications.

A. Energy Model:

Because the sensor nodes are responsible for a variety of tasks, including sensing, processing, and communicating. Consequently, taking into account all three functions, the overall energy consumption is assessed using the first-order energy model [6] in the work (1)

$$C_E = K_E + L_E + D_E \quad (1)$$

Whereas K_E describes energy required for performing sensing function, L_E describes energy required for performing processing function, and D_E describes energy required for performing communication function.

B. Unequal cluster formation and Cluster Head Selection:

Work executes an uneven cluster size, as seen in figure 1. Clusters that are geographically closer to the IoT gateway server have a lower cluster radius, while clusters that are geographically further away have a much larger cluster radius. The model is then able to eliminate first node death by addressing the hotspot concerns. Cluster head (CH) selection primarily aims to reduce power consumption and delay. The current approaches to CH selection use multi-objective optimisation, but they can't change on the fly to meet the IoT applications' real-time QoS demands. This study suggests a new weighted cost function to get around this restriction., K_y , for CH selection, as defined in Equation (2).

$$K_y = \frac{M_{\rightarrow} * \alpha}{(X_v * \beta) * (\epsilon * \gamma)} \quad (2)$$

Parameter α , β , and γ describes weight parameter, X_v describes number of neighboring sensor present within one-hop range, $\mathcal{E}$ is residual energy of the sensor, $M_{\rightarrow}$ define distance between the neighboring nodes which is measured in (3)

$$M_{\rightarrow} = K_h / \mathcal{A} \quad (13)$$

Here, K_h signifies total distance comparative to all sensor nodes, while $\mathcal{A}$ signifies distance to neighboring sensor nodes. IoT gateway server receives data on the position and remaining power of each sensor node. Next, the gateway server uses a cost function to identify nodes that will act as cluster heads (CHs). Node with highest value is chosen as CH, and any additional nodes that are within one hop of it are assigned to being members of the CH. Using Carrier Sense Multiple Access with Collision Avoidance (CSMA/CA), this method leverages intra-cluster optimisation for CH selection with a goal of minimising failures.

C. Routing Optimization:

Time-driven IoT application's member nodes start sensing operations when the cluster head (CH) is chosen, and then they use an optimised TDMA scheduling method to send the data they've acquired to their own CHs. By reducing contention overhead, TDMA improves communication efficiency.. Additionally, this study introduces L_M , an inter-cluster routing optimization technique based on a weighted multi-objective function, as defined in Equation (4).

$$L_M = (\mathcal{E}_v * w_1) + (\mathcal{G}_l * w_2) + (\bar{\mathcal{G}}_l * w_2) + (\mathbb{L}_l * w_3) \quad (4)$$

Wherein w_1 , w_2 , and w_3 describes IoT application specific dynamic QoS parameter optimization for residual energy $\mathcal{E}_v$, number of hops $\mathcal{G}_l$, and packet loss $\mathbb{L}_l$, respectively. In (4) the hop count is measured in (5)

$$\mathcal{G}_l = \sum_{t \in l} \mathcal{SD}(t) * \mathcal{DS}(t), \quad (5)$$

In (4), the inverse hop count is measured in (6)

$$\bar{\mathcal{G}}_l = \sum_{t \in l} \frac{1}{\mathcal{SD}(t) * \mathcal{DS}(t)}, \quad (6)$$

where the packet loss rate $\mathbb{L}_l$ in (4) is measured in (7)

$$\mathbb{L}_l = \prod_{t \in l} \mathcal{SD}(t) * \mathcal{DS}(t) \quad (7)$$

In this context, $\mathcal{SD}(t) * \mathcal{DS}(t)$ signifies data delivery ratio for IoT-WSN link in communication path l , where $\mathcal{SD}(t)$ signifies transmission from source to destination and $\mathcal{DS}(t)$ shows transmission from destination back to source. By utilizing L_M in Equation (4), every cluster head (CH) gains multiple routing paths for reaching IoT gateway server. After optimising routing process, suggested method chooses best route according to unique needs of IoT application. For time-sensitive IoT applications, ELBPFO model is ideal since it increases network lifespan, decreases total communication latency, and shortens routing pathways.

D. Algorithm:

With this technique, Internet of Things (IoT)-based WSN applications may optimise energy usage, balance

network traffic, and minimise packet failure. Wireless sensor networks (WSNs) powered by the Internet of Things (IoT) may benefit from the Energy-Aware Load Balanced Packet Failure Optimisation (ELBPFO) algorithm, which reduces communication latency while increasing energy efficiency. After the sensor nodes are initialised, the algorithm defines an energy model that takes into consideration the energy consumption of sensing, processing, and communication. In order to reduce the impact of hotspots, it uses uneven clustering, whereby clusters that are closer to the server of the IoT gateway have lower radii. When choosing a Cluster Head (CH), a weighted cost function is used that takes into account distance to neighbours, node density, and residual energy. TDMA scheduling and CSMA/CA for collision avoidance and efficient data transfer are used to optimise intra-cluster communication. In order to guarantee connectivity across clusters, the routing optimisation phase chooses the best routes according to factors including packet loss rate, hop count, and residual energy. To make sure the network lasts and is reliable, data is pooled at CHs and sent to the IoT gateway server via an optimised multi-hop routing method.

Time complexity of ELBPFO algorithm depends on its core components. The cluster formation process

involves broadcasting messages, leading to a complexity of $O(N)$, where N is the number of nodes. Cluster head selection requires computing the weighted cost function for all nodes, making it $O(N \log N)$ utilising sorting-based selection approach. Routing optimization involves computing path weights and selecting the optimal route, based upon number of CHs and potential paths. Using *Dijkstra's algorithm* or *A search**, the complexity

is $O(C^2)$, where C is number of CHs. TDMA scheduling within clusters operates in $O(N)$ time, as each node is assigned a time slot. Overall, the ELBPFO algorithm exhibits an approximate complexity of $O(N \log N + C^2)$, making it scalable for large IoT-based WSN deployments.

Algorithm 1: Energy-Aware Load Balanced Packet Failure Optimization (ELBPFO)

Step 1: Initialization

1. Deploy sensor nodes in the IoT-enabled WSN environment.
2. Assign each sensor node
 - Initial energy level $\mathcal{E}_v$
 - Location coordinates (x_i, y_i) .
 - Communication range R_i .

Step 2: Energy Model Definition

1. Define the total energy consumption using first order energy model

$$(C_E) = K_E + L_E + D_E$$

where

- K_E defines energy needed to perform sensing function
- L_E defines energy needed to perform processing function

D_E defines energy needed to perform communication function.

- To get the energy consumption per node, utilise first-order energy model utilising (1).

Step 3: Unequal cluster Formation

1. Divide the network into clusters:
 - Clusters' radius is decreased when they are located closer to IoT gateway server.
 - Radius is higher for clusters that are further away from server of IoT gateway
2. Broadcast cluster formation messages to sensor nodes.

Step 4: Cluster Head (CH) Selection

1. Each sensor node computes its weighted cost function

$$K_y = \frac{M_{\rightarrow} * \alpha}{(X_v * \beta) * (\mathcal{E} * \gamma)}$$

Where:

- The parameter α , β , and γ defines the weight parameter
 - X_v defines the number of neighboring sensor present within one-hop range
 - $\mathcal{E}$ is residual energy of the sensor
 - $M_{\rightarrow}$ define distance between the neighboring nodes
2. The node with the highest K_y value is selected as the CH.
 3. Other nodes within one-hop range join the CH.

Step 5: Intra-Cluster Communication Optimization

1. To stay clear of gearbox problems, use CSMA/CA.
2. To facilitate data transfer inside a cluster, set aside TDMA slots.

Step 6: Routing Optimization

1. Each CH computes a weighted multi-objective routing function:

$$L_{\mathcal{M}} = (\mathcal{E}_v * w_1) + (\mathcal{G}_l * w_2) + (\bar{\mathcal{G}}_l * w_3) + (\mathbb{L}_l * w_4)$$

Where:

- w_1 , w_2 , w_3 and w_4 defines the IoT application specific dynamic QoS parameter optimization for residual energy $\mathcal{E}_v$, number of hops $\mathcal{G}_l$, and packet loss $\mathbb{L}_l$, respectively.
- X_v defines the number of neighboring sensors present within one-hop range
- $\mathcal{E}$ is the residual energy of the sensor

- $\mathbb{L}_l$ defines packet loss rate

2. CH chooses best inter-cluster path to server of the IoT gateway.

Step 7: Data Transmission

- By use of TDMA, sensor nodes communicate the data they have detected to respective CHs.
- In order to send data via the most efficient inter-cluster channel, CHs compile it.
- The data is received and processed by the IoT gateway.

Step 8: Repeat Until Network Lifetime Ends

1. At the end of every communication cycle, update the nodes' energy levels.
2. Switch out CHs if their energy levels get too low.
3. When network is empty, repeat steps 4–7.

5 Work Carried Out So Far

The SENSORIA [14] simulator is used to conduct extensive simulations in order to assess the proposed ELBPFO model. The hardware components of the experimental setup include an NVIDIA 4GB CUDA GPU, 16 GB of RAM, a Pentium I7 CPU, and Windows 10. C# and the Visual Studio.NET framework 4.5 or later are used to implement the algorithm. In this study, we evaluate ELBPFO's performance under different network circumstances to that of two other models, dynamic LEACH-AHP (DLAHP) [5] and Hierarchal traffic offloading (HTO) [8]. We do extensive simulations in the SENSORIA simulator to test the ELBPFO model. An Intel Pentium i7 CPU, 16 GB of RAM, and an NVIDIA 4GB CUDA GPU make up the experimental environment, which runs Windows 10. C# and the Visual Studio.NET framework 4.5 or later are used to create and run the algorithm. We evaluate ELBPFO's performance under various network situations to that of Dynamic LEACH-AHP (DLAHP) and Hierarchical Traffic Offloading (HTO) models in order to determine ELBPFO's efficacy.

Various configurations of 250 (X-small), 500 (Small), 1000 (Medium), and 2000 (Large) sensor nodes are randomly placed inside a 50m × 50m network space for the simulations to run. Data collection from all sensor nodes is handled by a single base station (BS). With an initial energy of 0.05 to 0.2 Joules, each sensor node may transmit up to 5 meters and detect up to 3 meters. With 248 bits for control packets and 2000 bits for data packets, the energy usage per bit is 50 nJ. There is a 10,000 bps available bandwidth, yet the data transfer rate is 100 bps. The main instruments for sensing are temperature sensors. The energy needed to amplify the signal (Emp) is 100 pJ/bit/m², while the idle energy consumption (Eelec) is kept at 50 nJ/bit. A controlled environment is provided by this simulation setup to test the efficiency of ELBPFO across different network densities in terms of energy consumption, data transmission, and network performance.

A. Network Lifetime:

The duration until the first sensor node runs out of power is known as the First Node Death (FND) and is used to measure the network lifespan. As seen in Figure 2, a longer FND time suggests a more effective distribution of energy across the sensor nodes. To make sure that nodes close to the base station don't run out of juice too fast, the ELBPFO model uses uneven clustering and adaptive cluster head (CH) selection to optimise power usage. The energy-aware routing method and balanced load distribution in ELBPFO allow it to outlast Dynamic LEACH-AHP (DLAHP) by 84.78% and Hierarchical Traffic Offloading (HTO) by 57.3%.

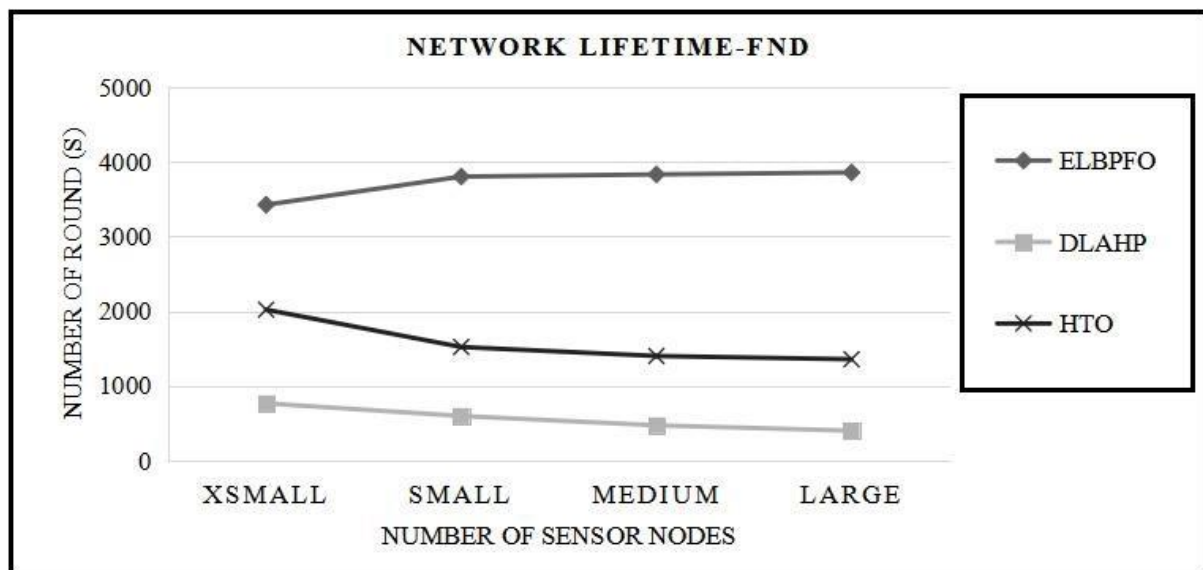


Fig. 2. Network lifetime vs varied sensor devices.

B. Control channel Overhead:

Cluster creation, CH selection, and routing changes incur additional communication and signalling messages known as control channel overhead. Figure 3 shows that high overhead may lead to decreased network efficiency and increased energy usage. By employing an optimised TDMA-based intra-cluster communication and a weighted cost function for CH selection, ELBPFO minimises control overhead by minimising unnecessary message exchanges. The findings demonstrate that ELBPFO is more suited for large-scale deployments due to its reduced control overhead compared to DLAHP and HTO, which is 23.99% and 12.6% lower, respectively.

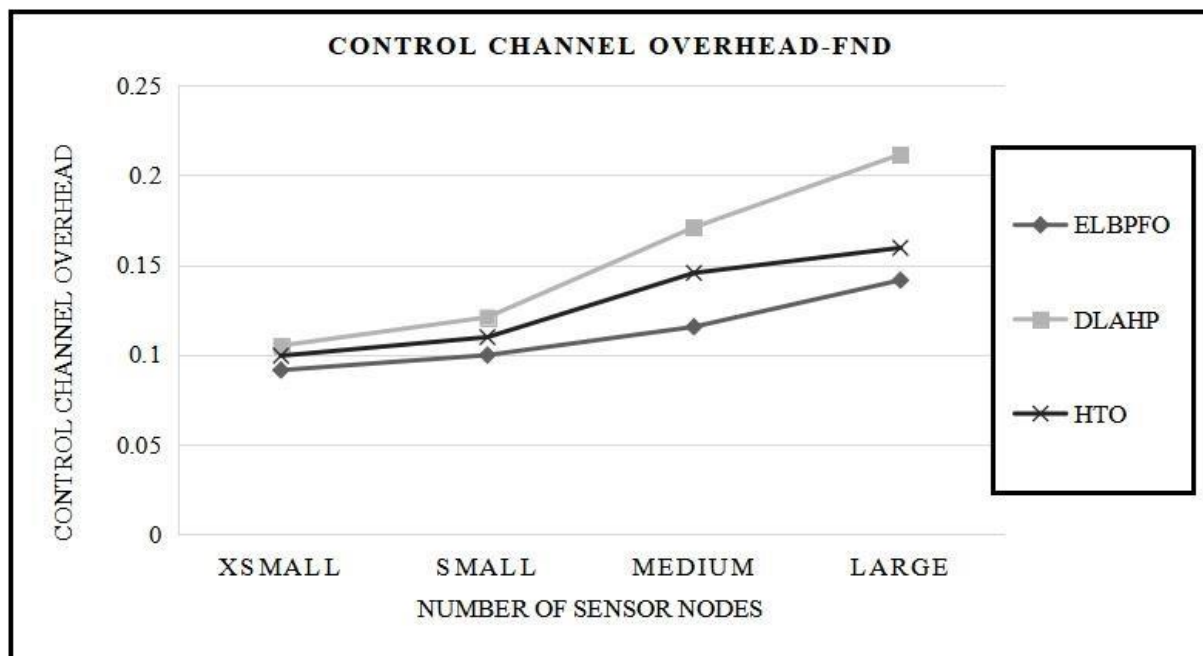


Fig. 3. Communication Overhead vs varied sensor devices.

C. Throughput Performance:

Rate of data packets that make it across a network is called throughput. A higher throughput number suggests that data is being sent efficiently with less packet loss. Figure 4 shows that ELBPFO's optimised routing

system, which chooses pathways depending on residual energy, hop count, and packet loss rate, leads to greater throughput than the baseline models. Furthermore, TDMA scheduling and collision avoidance methods (CSMA/CA) also enhance the efficiency of packet delivery. Findings show that ELBPFO maintains a steady and high throughput better than DLAHP and HTO, with a performance gap of 58.5% and 12.8%, respectively, especially in crowded network settings.

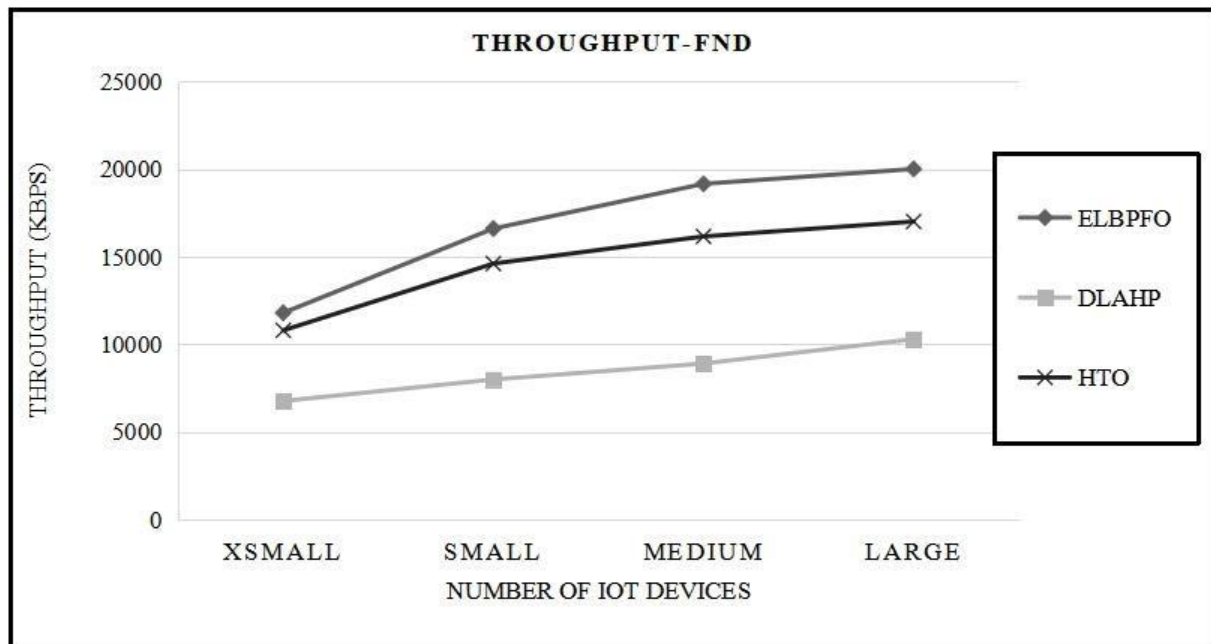


Fig. 4. Throughput vs varied sensor devices.

6 Conclusion

In terms of energy efficiency, network longevity, delay minimisation, data reliability, and standard clustering-based routing protocols, this study's results show that ELBPFO model is much superior. For time-sensitive Internet of Things (IoT) applications, ELBPFO is an excellent choice because it delivers a balanced trade-off amongst latency and energy consumption via the use of optimised TDMA scheduling, adaptive multi-objective routing, and weighted cluster head selection. In order to guarantee scalability and resilience in large-scale IoT-WSN installations, simulation findings show that ELBPFO increases network lifetime, decreases power consumption, and minimises transmission delays. Because of its flexible architecture, it can adapt to changing network circumstances and make good use of available resources. To improve the overall flexibility and performance of the network, future research may investigate soft-soft computing approaches to hone cluster head selection and routing choices even further.

7 Future work to be carried out

Following will be considered for development in future work:

- In order to guarantee energy efficiency and dependability in IoT applications provided by sensor networks, future work will include designing Joint Routing and Resource Optimisation utilising a soft-computing paradigm.

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