Modified Butterfly Optimization Algorithm based Energy Efficient Routing Protocol for Internet of Things Environment

[1]Gayathri A, [2]Dr.Sasikumar S
[1]Research Scholar, Dept.of Electrical Engineering, Faculty of Engineering and Technology, Annamalai University,Annamalai Nagar, Chidambaram.
[2]Associate Professor, Dept.of Electrical Engineering, Faculty of Engineering and Technology, Annamalai University, Annamalai Nagar, Chidambaram.
gayathri.network@gmail.com

Abstract

Internet of Things (IoT) devices can be usedfor sensing the atmosphere, gathering data and sending them to the locations and base station (BS) utilized for analysis. In WSNs for IoT, intellectual routing was asignificant criterionmandated to enrich the Quality of Service (QoS) in the network. Additionally, the energy demanded transmission in the IoT assistedsensor networks will be difficult to ignore immense packet drop or packet loss, unfairness and rapid energy depletion over the network causingreduction in node performance and surge in delay with regard to packet delivery. With this motivation, this article introduces a Modified Butterfly Optimization based Energy Efficient Routing Protocol (MBFO-EERP) for IoT environment. The presented MBFO-EERP technique chooses an optimal set of routes to destination in the IoT assisted WSN. To accomplish this, the MBFO-EERP technique follows random node deployment and node initialization processes. In addition, the presented MBFO-EERP technique integrates the concept of Levy flight (LF) into the conventional BFO algorithm. Moreover, the fitness function of the MBFO-EERP technique integrates three input parameters such as intra-cluster distance, inter-cluster distance, and residual energy. To exhibit the enhancedefficiencyof the MBFO-EERP system, a wide-ranging simulation analysis is performed. The extensive outcomesshowthe betterment of the MBFO-EERP method over other measures.

Keywords: Internet of Things; Wireless sensor network; Energy efficiency; Routing protocol; Fitness function
DOI Number: 10.48047/nq.2022.20.8.NQ221028 **NeuroQuantology 2022; 20(22): 10069-10086**

1. Introduction

Internet of Things (IoT) can be defined as a novel computing facility which comprises features from software devices and networks it helps to connect multiple gadgets for coordinated working [1]. The model of IoT should handle difficulties about communication and interconnection. The prevailing protocols modelled for wireless, wired, and sensor networks cannot be utilized directly to enhance the efficiency of IoT related networks because of heterogeneous gadgets which include larger house hold devices and tiny devices [2]. There are several applications in daily life in which we use sensors, mobile phones, house hold devices, and laptops like air microwave ovens, conditioners, fridges, washing machines, and coffee makers that are gathered with IoT for executing several actions [3]. Additionally, IoT is used with our vehicles utilizing vehicular adhoc networks (VANETs) and it can be utilized for data collection routing and a quantity of intelligence is presented in IoT for effectual communication and co-ordination [4].

Current advances in the IoT and WSN simplifies the machine and computer self-dictating procedure to control and monitor automation of industry without involvement of human [5]. It even has incredible advantages like increasing product quality and productivity minimalizing routine checks and enriching safety standards reducing the requirement for labor and cycle times, thus lessening operating costs [6]. But, battery operated WSNs are cheaper and renders continuous supply of power to activate the sensor modules [7]. And as well, it offers continual services to the IoT. Yet, the energy consumption of batteries remains the performance limiting component in WSN, since it is hard to recharge or replace the battery while utilizing the sensor in machine parts [8]. Owing to energy limitations of sensor nodes (SNs), it is vital to expand the network lifespan in an industry. Numerous authors recommended methods for energy-efficient routing for WSNs. But how to route and process the data with potential usage of battery power to the destiny remains a problem [9]. In the dispersed routing techniques, all nodes made decisions separately depending on local information instead of global knowledge of the networks. Certain existing routing protocols solved source originated on-demand routing, where source nodes-initiated route to the destiny whenever it desired to transfer the data, but it even had high overhead control and time complexities [10].

This article introduces a Modified Butterfly Optimization based Energy Efficient Routing Protocol (MBFO-EERP) for IoT environment. The presented MBFO-EERP technique chooses an optimal set of routes to destination in the IoT assisted WSN. To accomplish this, the MBFO-EERP technique follows random node deployment and node initialization processes. In addition, the presented MBFO-EERP technique integrates the concept of Levy flight (LF) into the conventional BFO algorithm. Moreover, the fitness function of the MBFO-EERP technique integrates three input parameters such as intra-cluster distance, inter-cluster distance, and residual energy. To demonstrate the enhanced efficiencyof the MBFO-EERP method, a wide-ranging simulation analysis was performed.

2. Related Works

Seyfollahi et al. [11] represented a technique called hybrid energy-aware protocol for data routing in IoT platforms. It is positioned depending on metaheuristic HTOA (Heat Transfer Optimizer) and Machine Learning (ML). The presented protocol adopted a four-stage technique for fuzzy clustering, forecasting power utilization relevant to time series methods and SVR, choosing the best CH consideration of energy and centralization elements, and routing and data communication from all sensors to and from CH to sink utilizing ACO technique. Lakshmanna et al. [12] introduced an IMD-EACBR technique abbreviated as improved metaheuristic-driven energy-aware cluster-related routing method for IoT-based WSNs. This IMD-EACBR method aims to reach higher power utilization and network lifespan. In order to reach this, the abovementioned method initialy devises an improved AOA - oriented clustering (IAOAC) method for cluster organization and CH election. Furthermore, TLBO technique -related multi-hop routing (TLBO-MHR) method can be implemented for choosing best routes to destinations.

A reliable and trustworthy inter-correlated routing technique related to BC, Meta-heuristic, and DL methods was presented in [13]. The disseminated routing information in WSN was managed by BC method, where the optimal routing was executed through Salp Swarm Optimizer technique. The routing info variations among nodes were envisioned and best routing decisions were executed through the Deep CNN technique. The authors [14] devise a new chaotic bumble bee mating optimizer (CBBMO) technique for secure data communication including trust sensing method, named CBBMOR-TSM technique. The core objective of the aforementionedtechnique was to devise a trust sensing model and do secure routing with the use of the CBMO technique. The presented approach originally devises a trust sensing method by including direct and indirect trust that can be used for determining the trusted values of IoT nodes so that malevolent nodes are detected.Cano et al. [15] intend to curtail the travel hours in multi-block high-level storage mechanisms considering height level constraints to choose gadgets to leave aisles. Through consideration of such operating atmospheres, formulation of minimal travel times amongst each pair of storage places can be modelled and picker routing problem (PRP) was resolved with the use of ACO and GA. In [16], an efficient energy method can be devised for routing on the IoT where focus was on the sleep–wake schedule of nodes; thus, a novel optimized technique named chaos fuzzy grasshopper optimizer approach has been exploited. In this system, through Lorenz chaos theory, the initial population of grasshoppers was modelled and the output and input variables of the system will be adjusted by fuzzy method. Praveen and Prathap [17] devise an ECRR method i.e., energy efficient congestion aware resource allocation (RE) and routing protocol for IoT platform depends on hybrid optimized methods to figure out the issue of both RE and routing. The initial contribution of presented ECRR system was to use the metaheuristic and data clustering system to allot the large-scale gadgets and gateways of IoTs for minimizing total congestion among them. The secondary contribution was to devise a queue related swarm optimized system to elect an optimal route for future routes constructed on many limitations, which enriches route discovering mechanism.

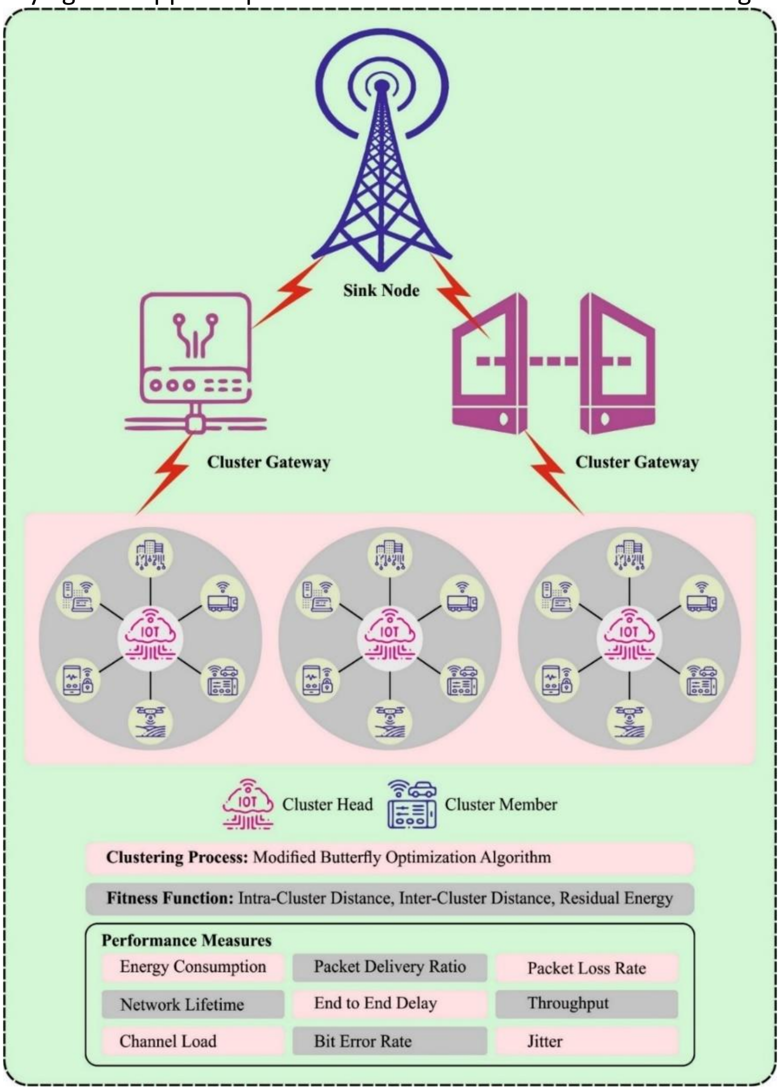

Fig. 1. Overall process of MBFO-EERPsystem

3. The Proposed Model

In this article, we have developed a new MBFO-EERP method for selecting the optimal set of routes to destination in the IoT assisted WSN. To accomplish this, the MBFO-EERP technique followed the random node deployment and node initialization process. In addition, the presented MBFO-EERP technique integrated the concept of LF into the conventional BFO algorithm. Fig. 1 demonstrated the overall procedureof MBFO-EERP algorithm.

3.1. System Model

The study presented a system method, along with the energy consumption model, and IoT performance criteria [18].

IoT Model

In this study, the IoT as $T = (N, L)$ was modelled, where N and Lwere regarded as a IoTgadgets, and transmission links, correspondingly. The dimension of the monitoring region is regarded as $H \times W$, and a sink was deployed in center of it. Heterogeneous devices with dissimilar initial energy and communication radius were randomly scattered with uniform distribution throughout the monitoring region. In addition, it can be assumed every device d_i has certain properties given in the following:

- ON_i: The set of one-hop neighbors for each device $d_i$was demonstrated as ON_i. The device d_i has the certain communication radius r_i. IoTgadgets, which their Euclidean distance from d_i is lesser than r_i, were regarded as a one-hop neighbors.
- E_i: represent the RE of $d_i$device, at any time. All the devices have a specific quantity of energy at the system initialization that can be exhausted by sending or receiving packets and data processing methods. With regard to the above mentioned, the sink has limitless energy, at any moment.
- V_i: The data volume produced by d_i device was demonstrated as V_i that is another fundamental criterion to optimally cluster IoTgadgets.A CH expire its energy faster, once the amount of data produced by the member is higher. Therefore, reduces the system's lifetime.
- $D_{i,Sink}$: The Euclidean distance between d_i device and sink wererepresented as $D_{i,Sink}$ that is a significant criterion to choose near-optimum CHs. Lastly, it is regarded that device was grouped into k cluster.
- D_{ij}: The Euclidean distance amongd_i and d_j devices are represented as D_{ij} that is a leading criterionto choose near- optimum CHs and give effective cluster.

Energy model

In the study, the energy consumption mechanism has been used that carries out according to the Euclidean distance among network equipment. Device d_i could transfer data to d_j, if their Euclidean distance was lesser than r_i. In addition, for an effective broadcast on the connection amongd_i and d_j,IoT device that is placed in interference range of d_j could not transfer data at the same time. It modelled the energy consumption as free space or multipath fading channel. Thus, the method assesses the essential energy for 1-bit data transmission over model as follows:

$$E_{\tau r}(1, D_0) = \begin{cases} 1E_{elec} + 1\varepsilon_{fs} D_{ij}^2 & D_{ij} < D_0 \\ 1E_{elec} + 1\varepsilon_{emp} D_{ij}^4 & otherwise \end{cases} \quad (1)$$

Where E_{elec} denotes the energy depletion of the electrical circuit; ε_{fs} and ε_{mp} denotes the energy depletion of amplifier in the free space and multipath fading channels, correspondingly. In addition, energy depletion for 1-bit data receiving is evaluated by:

$$E_{re}(1) = 1E_{elec} \quad (2)$$

3.2. Design of MBFO Algorithm

BFO is motivated by the food foraging behavior of the butterfly and is exploited as a searching agent to implement optimization [19]. Butterflies (BFs) have a sense receptor which is used to sense or smell the fragrance of flowers or food. This sense receptor is called chemoreceptor and is disseminated over the parts the body. The proposed technique assumes that the BF generates

10072

fragrance or odor with specific concentration or power. The fragrance that increases from the BF can be sensed by the various butterflies presented in the neighborhood and an aggregate social learning system is framed. This fragrance is associated with the fitness of BF that is estimated by the objective function. This characterizes that once the BF moves around in the searching region, the fitness could have similarly changed. If the BF cannot identify the scent of others in the searching space, later makinga random stride and this is called a local searching technique. Next, once the BF sense the odor concentration from optimal BF in the searching region, it moved to the optimal BF that is termed a global search process and it is expressed by Eq. (3):

$$pf_i = cI^a, \tag{3}$$

Now, c indicates the sensory modality, a denotes the power exponent based on modality that is responsible for various levels of absorption, pf_i, describe the perceived magnitude of perfume viz., how intensely the odor of i^{th} butterflies are observed by other butterflies existing in the region, and I illustrates the stimulus intensity.

$$x_{i^{t+1}} = x_{i^t} + F_i^{t+1}, \tag{4}$$

Now, F_i signifies the fragrance that is exploited by x_i^{th} butterflies for upgrading the location in the process of iterations and x_i^t signifies the solution vector for i^{th} butterflies at t iteration amount. Also, there exist two major phases, global and local search techniques. In the global search process, the BF take a step closer to the proper solution or BF g^* using the following equation:

$$F_i^{t+1} = \left(r^2 \times g^* - x_{\mathrm{i}}^t\right) \times pf_i, \tag{5}$$

Here, g^* indicates the present optimal solution among the current iterations, pf_i signifies the perceived fragrance of i^{th} butterflies and r is the randomly generated value within [0,1]:

$$F_i^{t+1} = \left(r^2 \times x_{j^t} - x_{k^t}\right) \times pf_i, \tag{6}$$

Where, x_{j^t} and x_{k^t} characterizes j^{th} and k^{th} BF from the solution space. When x_{j^t} and x_{k^t} belongs to the equivalent population and r is the randomly generated value within [0,1]. A switching possibility p is exploited in BFO to switch from global searching to intensive local search space. The pseudocode of BFO has been illustrated in Algorithm 1.

In the MBFO, the BFO is incorporated with the concept of Levy Flight (LF). The LF monitor the rules of the Levy distribution of arbitrary phenomena such as Brownian motion, random walk, etc. Currently, LF is widely exploited in intelligent optimization. For example, the BFO carries out LF to update the location. LF presents the searching space, thereby it becomes simple to prevent early convergence by presenting LF into the MBO technique. Fig. 2 defines the steps involved in MBFO.LF location upgrades are as follows:

$$x_i(t+1) = \begin{cases} x_j(t) + \alpha \oplus Levy(\lambda) & f\left(x_j(t)\right) \le f\left(v_i(t+1)\right) \\ v_i(t+1) & f\left(\chi_i(t)\right) > f\left(v_i(t+1)\right) \end{cases}, \tag{7}$$

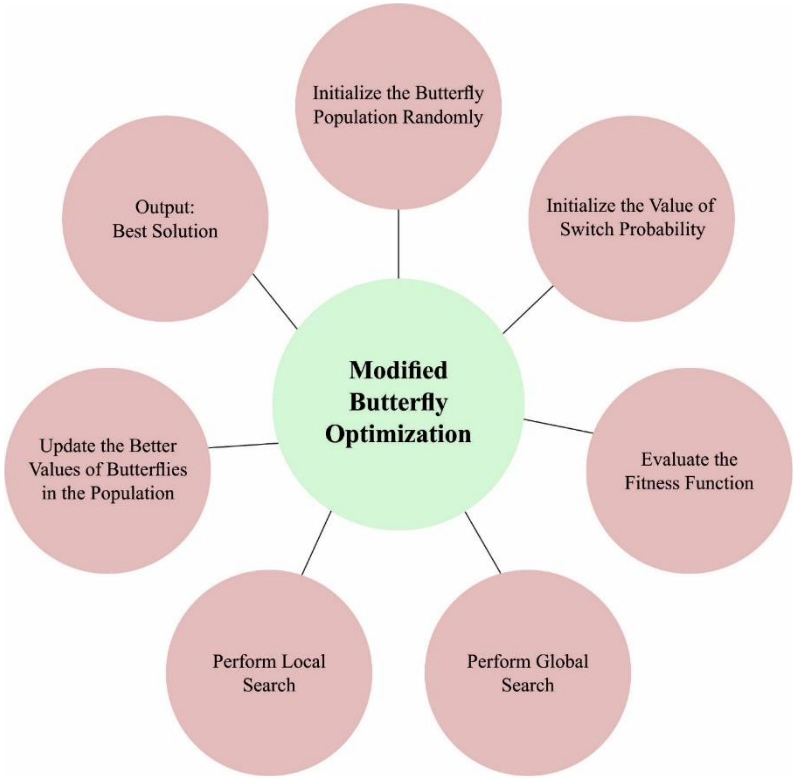

Fig. 2. Steps involved in MBFO

In Eq. (7), x_i^t describes the t^{th} generation location of x_i,$\oplus$ denotes the dot multiplication, α shows the step size control parameter, and Levy (λ) represents the arbitrary searching path that achieves:

$$Levy \sim u = t^{-\lambda}, 1 < \lambda \leq 3, \quad (8)$$

The step size perceives the Levy distribution, and step size s is evaluated by:

$$s = \frac{\mu}{|v|^{1/\beta}}, \quad (9)$$

Where μ, v are uniformly distributed as follows:

$$\mu \sim N(0, \sigma_\mu^2), \quad (10)$$

$$v \sim N(0, \sigma_v^2), \quad (11)$$

Whereas

$$\sigma_\mu = \frac{(1+\beta)(\sin\frac{\pi\beta}{2})}{\frac{1+\beta}{2}\beta^{2\frac{\beta-1}{2}}}, \quad (12)$$

$$\sigma_v = 1, \quad (13)$$

Now β is usually a constant of 1.5.

Algorithm 1: Pseudocode for BFO Algorithm

The major function $\mathrm{f(x)}, \mathrm{x} = (x_1, x_2 x_d)$
Produce the population of n butterflies $\mathrm{x_i} = (i = 1,2\ n)$
Define the switch probability p, sensor modality c, and power exponent a
While termination conditions are not fulfilled do
    for all the BFs from the population do
        Evaluate the odor concentration to BFs according to Eq.(3)
    end for
    Determine the optimal BF
    for all the BFs from the population do
        Produce the arbitrary integer within [0,1]
        if $rand < p$ then
            Move nearer the optimum BF

```
            else
                        Move arbitrarily according to Eqs. (4) and (6)
            end if
            Asses the novel BF
            If the novel BF is optimum, upgrade it from the population
      end for
      Upgrade the value of c
      Determine the current global best BF
end while
Output the better solution.
```

3.3. Process involved in MBFO-EERP Technique for Route Selection

The fitness function of the MBFO-EERP method integrates three input parameters such as intra-cluster distance, inter-cluster distance, and residual energy [20]. A multi-objective fitness function is exploited to optimally route and provides QoS parameter. The key parameter of the fitness function includes the remaining energy of the nodes, distanceamong nodes, the distance to the hole, and the energy predictable to send packet from the next hop to hole. The distance to sink and distance between nodes is determined in the following:

$$D_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}, \tag{14}$$

$$DS_i = \sqrt{(x_i - x_{\text{sink}}\ )^2 + (y_i - y_{\text{sink}})^2}, \tag{15}$$

In the expression, x_i indicates the sensor longitude i, y_i denotes the sensor latitude i, and i and j were the sensors and it is followed by: 10075

$$E_{TX}(l, d_{ij}) = E_{elec} * l + E_{amp}(d_{ij}) * l = \begin{cases} E_{elec} * l + \varepsilon_{fs} * l * d_{ij}^2 & if\, d_{ij} < d_0, \\ E_{elec} * l + \varepsilon_{mp} * l * d_{ij}^4 & if\, d_{ij} \geq d_0, \end{cases} \tag{16}$$

Where $Elec$ indicates the energy needed for conducting and controlling electronic components; $E_{amp}(d_{ij})$ characterizes the energy utilized by amplifying the signal while transferring l-bit dataset (l signifies the amount of bits in the packet); ε_{fs} and ε_{mp} shows factor of open space model and multistep models, correspondingly; and d_{ij} represent the distance threshold that can be evaluated by:

$$d_0 = \sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{mp}}}. \tag{17}$$

The fitness function of the presented technique can be determined by.

$$\begin{aligned} Ming \ &= \sum_{i,j=1}^{n} D_{ij} + \sum_{i=1}^{n} D\,S_i + \sum_{i,j=1}^{n} E_{TXij} - \sum_{i,j=1}^{n} E_i, \\ &Subjected\ to \sum_{i=1}^{n} D_i \leq DS_i, \\ &\sum_{i=1}^{n} D\,S_{i-1} \leq DS_i, \\ &\sum_{i=1}^{n} E_{TXij} \leq \sum_{i=1}^{n} \sum_{k=1}^{m} \frac{E_{TXik}}{k}, \\ &\sum_{i,j=1}^{n} E_i \leq E_{Tota1}, \end{aligned} \tag{18}$$

Where D_i indicates the distance from the source nodes to the following hop, DS_i represents the evaluated distance from next hop to the destiny nodes, and E remaining energy of node in the IoT. The source node in all the steps evaluates the factor of distance to the adjacent nodes, distance to the destination, RE from the adjacent nodes, and channel quality amongst the value obtained and the selected neighboring nodes. It evaluates the fitness function for adjacent nodes and chooses the subsequent hop in local partial solution. Choosing an optimum partial solution in the path from source to destination nodes might result in optimum global routing.

4. Result Analysis

In this section, the routing performance of the MBFO-EERP technique can be examined in detail. In Table 1 and Fig. 3, brief ECM outcomes of the MBFO-EERP technique are investigated with other existing models [18, 21]. The experimental values signify that the MBFO-EERP technique reaches improvised results over other models. For instance, with 100 IoT nodes, the MBFO-EERP technique gains least ECM of 17mJ while the HEED, FRLDG, FEEC-HR, MetaH-C, and ABC-DC models attain reducing ECM of 151mJ, 132mJ, 77mJ, 67mJ, and 51mJ correspondingly. Simultaneously, with 500 IoT nodes, the MBFO-EERP technique gains least ECM of 109mJ while the HEED, FRLDG, FEEC-HR, MetaH-C, and ABC-DC models attain reducing ECM of 268mJ, 230mJ, 208mJ, 175mJ, and 149mJ correspondingly.

Table 1 ECM analysis of MBFO-EERP method with other systems underchanging IoT nodes

Energy Consumption (mJ)						
Number of IoT Nodes	**HEED**	**FRLDG**	**FEEC-HR**	**MetaH-C**	**ABC-DC**	**MBFO-EERP**
100	151	132	77	67	51	17
200	179	154	122	92	70	41
300	217	173	152	123	92	66
400	252	206	186	153	126	81
500	268	230	208	175	149	109

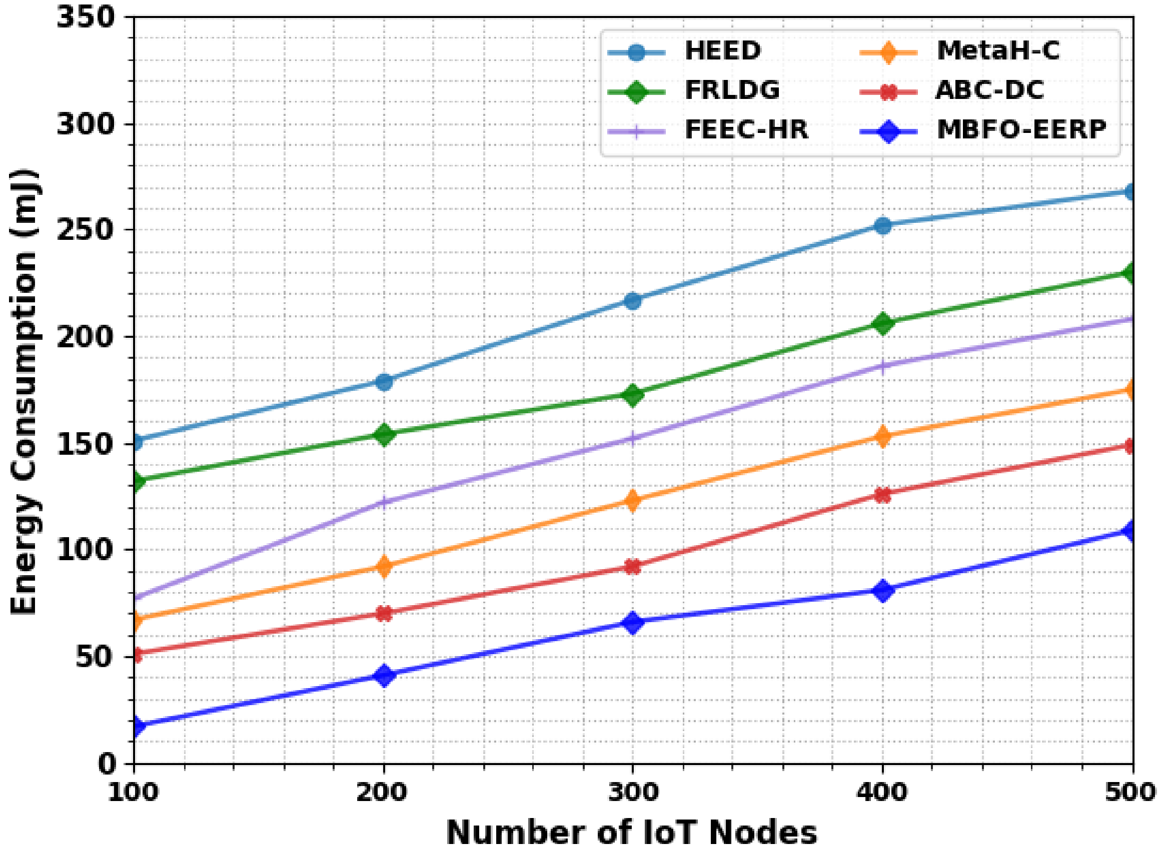

Fig. 3. ECM analysis of MBFO-EERP approach under varying IoT nodes

The detailed PDR examination of the MBFO-EERP technique with recent methods in Table 2 and Fig. 4. The outcomes represented that the MBFO-EERP method obtain increased values of PDR under all nodes. For example, with 100 IoT nodes, the MBFO-EERP system accomplish improvising PDR of 99.26% while the HEED, FRLDG, FEEC-HR, MetaH-C, and ABC-DC techniques reach decreased PDR of 89.55%, 91.75%, 94.01%, 96.33%, and 98.03% respectively.

Table 2 PDR analysis of MBFO-EERP method with other techniques under varying IoT nodes

Packet Delivery Ratio (%)						
Number of IoT Nodes	**HEED**	**FRLDG**	**FEEC-HR**	**MetaH-C**	**ABC-DC**	**MBFO-EERP**
100	89.55	91.75	94.01	96.33	98.03	99.26
200	89.55	91.62	94.13	95.78	97.24	99.13
300	88.75	90.65	93.64	94.55	96.63	99.26
400	88.21	89.79	90.46	93.76	95.29	99.26
500	85.09	86.62	90.53	92.60	94.98	97.36

Furthermore, with 500 IoT nodes, the MBFO-EERP technique accomplish improvising PDR of 97.36% while the HEED, FRLDG, FEEC-HR, MetaH-C, and ABC-DC techniques reach decreased PDR of 85.09%, 86.62%, 90.53%, 92.60%, and 94.98% correspondingly.

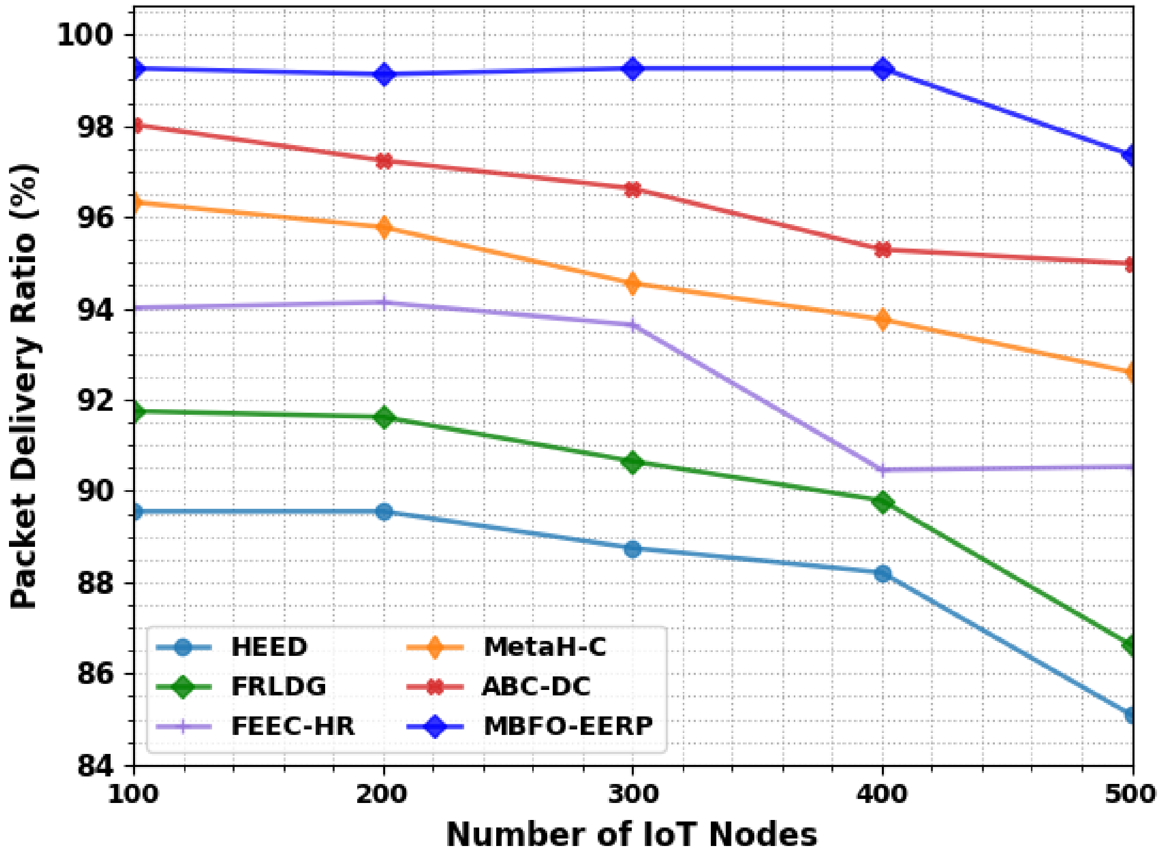

Fig. 4. PDR analysis of MBFO-EERP method under varying IoT nodes

In Table 3 and Fig. 5, a brief PLR outcome of the MBFO-EERP technique is investigated with other existing models. The experimental values signify that the MBFO-EERP technique reaches improvised results over other methods. For example, with 100 IoT nodes, the MBFO-EERP approach gains least PLR of 0.74% while the HEED, FRLDG, FEEC-HR, MetaH-C, and ABC-DC methods attain reducing PLR of 10.45%, 8.25%, 5.99%, 3.67%, and 1.97% respectively. Simultaneously, with 500 IoT nodes, the MBFO-EERP approach reaches least PLR of 2.64% while the HEED, FRLDG, FEEC-HR, MetaH-C, and ABC-DC methods have reducing PLR of 14.91%, 13.38%, 9.47%, 7.40%, and 5.02% correspondingly.

Table 3 PLR analysis of MBFO-EERP approach with other techniques under varying IoT nodes

Packet Loss Rate (%)						
Number of IoT Nodes	**HEED**	**FRLDG**	**FEEC-HR**	**MetaH-C**	**ABC-DC**	**MBFO-EERP**
100	10.45	8.25	5.99	3.67	1.97	0.74
200	10.45	8.38	5.87	4.22	2.76	0.87
300	11.25	9.35	6.36	5.45	3.37	0.74
400	11.79	10.21	9.54	6.24	4.71	0.74
500	14.91	13.38	9.47	7.40	5.02	2.64

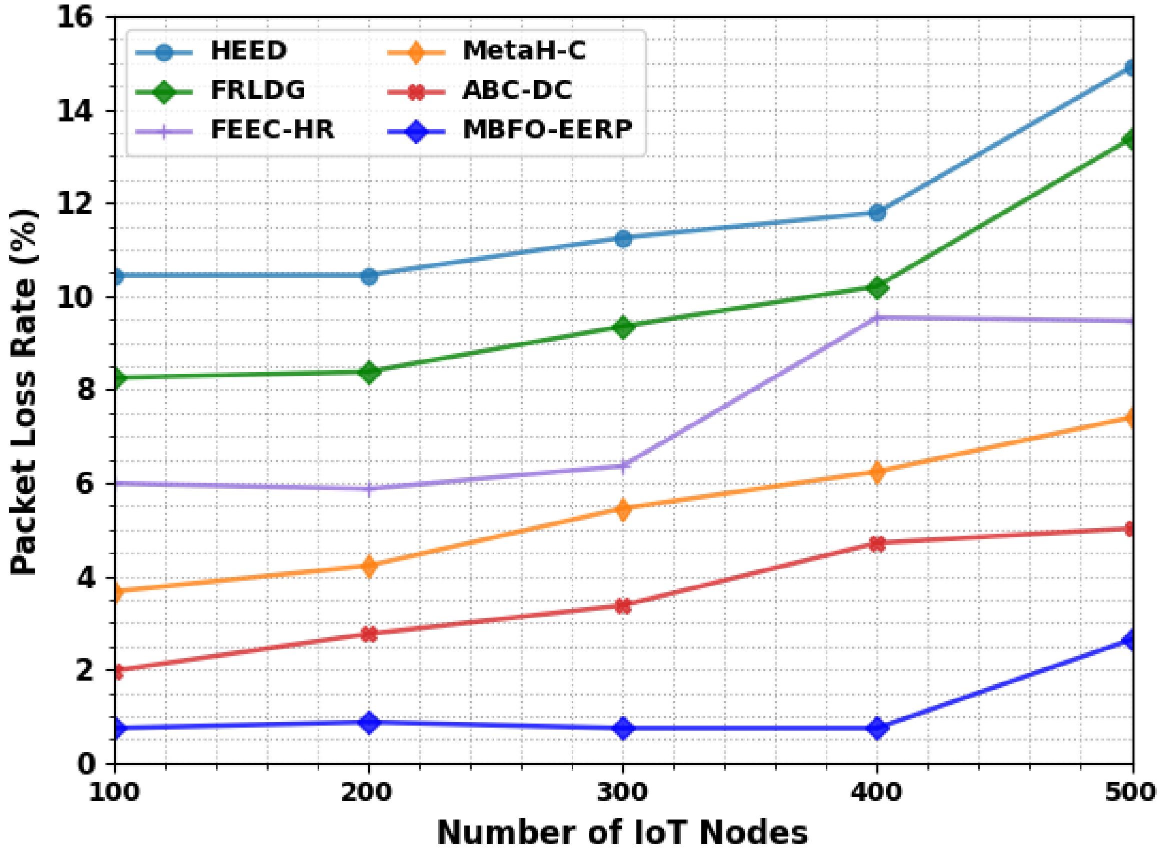

Fig. 5. PLR analysis of MBFO-EERP method under varying IoT nodes

The detailed NLT inspection of the MBFO-EERP system with recent models in Table 4 and Fig. 6. The outcomes represented that the MBFO-EERP system obtain increased values of NLT under all nodes. For instance, with 100 IoT nodes, the MBFO-EERP algorithm accomplish improvising NLT of 5771 rounds while the HEED, FRLDG, FEEC-HR, MetaH-C, and ABC-DC methods reach decreased NLT of 3830, 4139, 4536, 5006, and 5418 rounds techniques. Moreover, with 500 IoT nodes, the MBFO-EERP method accomplish improvising NLT of 5396 while the HEED, FRLDG, FEEC-HR, MetaH-C, and ABC-DC methods reach decreased NLT of 3337, 3587, 3852, 4492, and 4933 rounds correspondingly.

Table 4 NLT analysis of MBFO-EERP approach with other systems under changing IoT nodes

Network Lifetime (Rounds)						
Number of IoT Nodes	**HEED**	**FRLDG**	**FEEC-HR**	**MetaH-C**	**ABC-DC**	**MBFO-EERP**
100	3830	4139	4536	5006	5418	5771
200	3830	4146	4514	4984	5426	5720
300	3741	3999	4344	4911	5323	5646
400	3609	3705	3984	4631	5212	5565
500	3337	3587	3852	4492	4933	5396

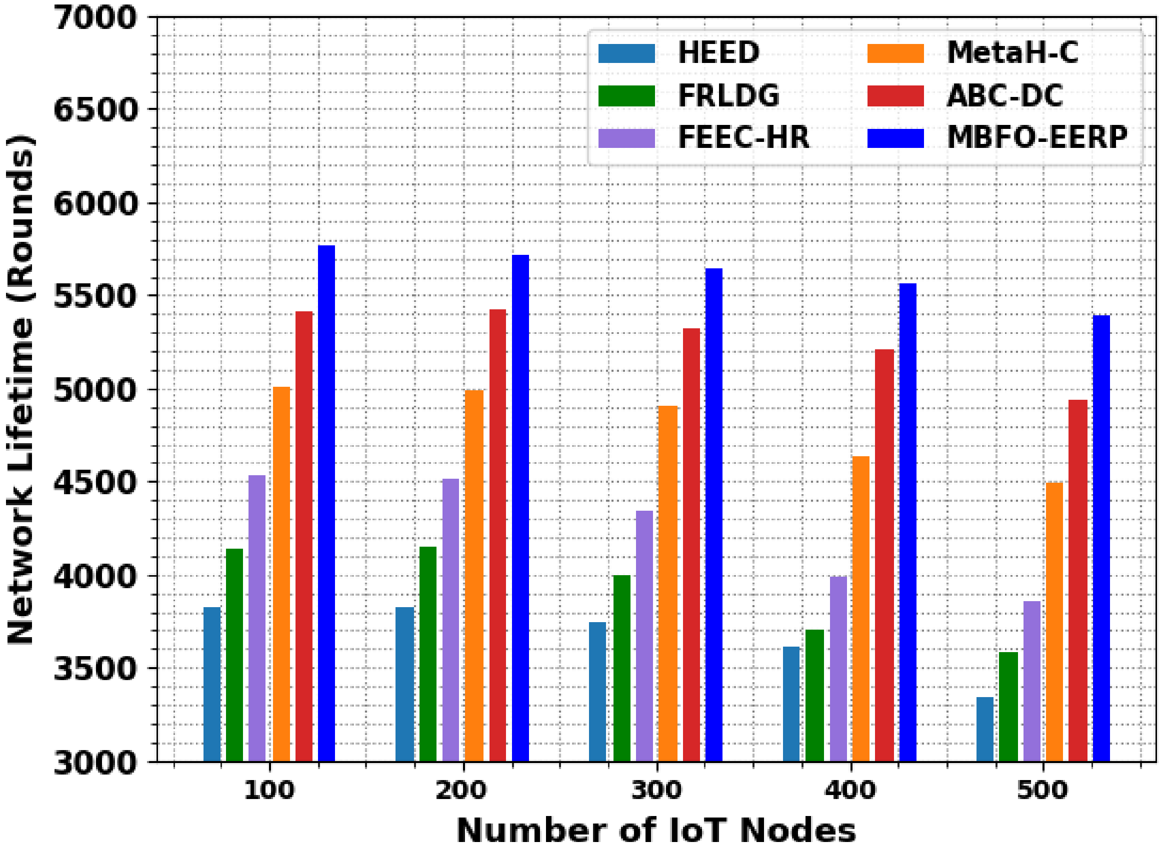

Fig. 6. NLT analysis of MBFO-EERP approach under varying IoT nodes

In Table 5 and Fig. 7, brief ETED outcomes of the MBFO-EERP system is investigated with other existing methods. The figure signifies that the MBFO-EERP method reaches improvised results over other methods. For example, with 100 IoT nodes, the MBFO-EERP method achieves least ETED of 1.32s while the HEED, FRLDG, FEEC-HR, MetaH-C, and ABC-DC approaches have reduced ETED of 6.85s, 6.29s, 5.68s, 4.06s, and 2.41s correspondingly. Next, with 500 IoT nodes, the MBFO-EERP system obtains least ETED of 5s while the HEED, FRLDG, FEEC-HR, MetaH-C, and ABC-DC methods attain reducing ETED of 11.17s, 10.44s, 9.38s, 8.17s, and 6.15s correspondingly.

Table 5 ETED analysis of MBFO-EERP approach with other mechanism under changing IoT nodes

End to End Delay (sec)						
Number of IoT Nodes	**HEED**	**FRLDG**	**FEEC-HR**	**MetaH-C**	**ABC-DC**	**MBFO-EERP**
100	6.85	6.29	5.68	4.06	2.41	1.32
200	8.82	6.91	6.03	4.56	3.53	2.35
300	10.32	7.88	7.09	5.53	4.23	3.32
400	11.17	9.26	8.41	7.32	5.59	3.79
500	11.17	10.44	9.38	8.17	6.15	5.00

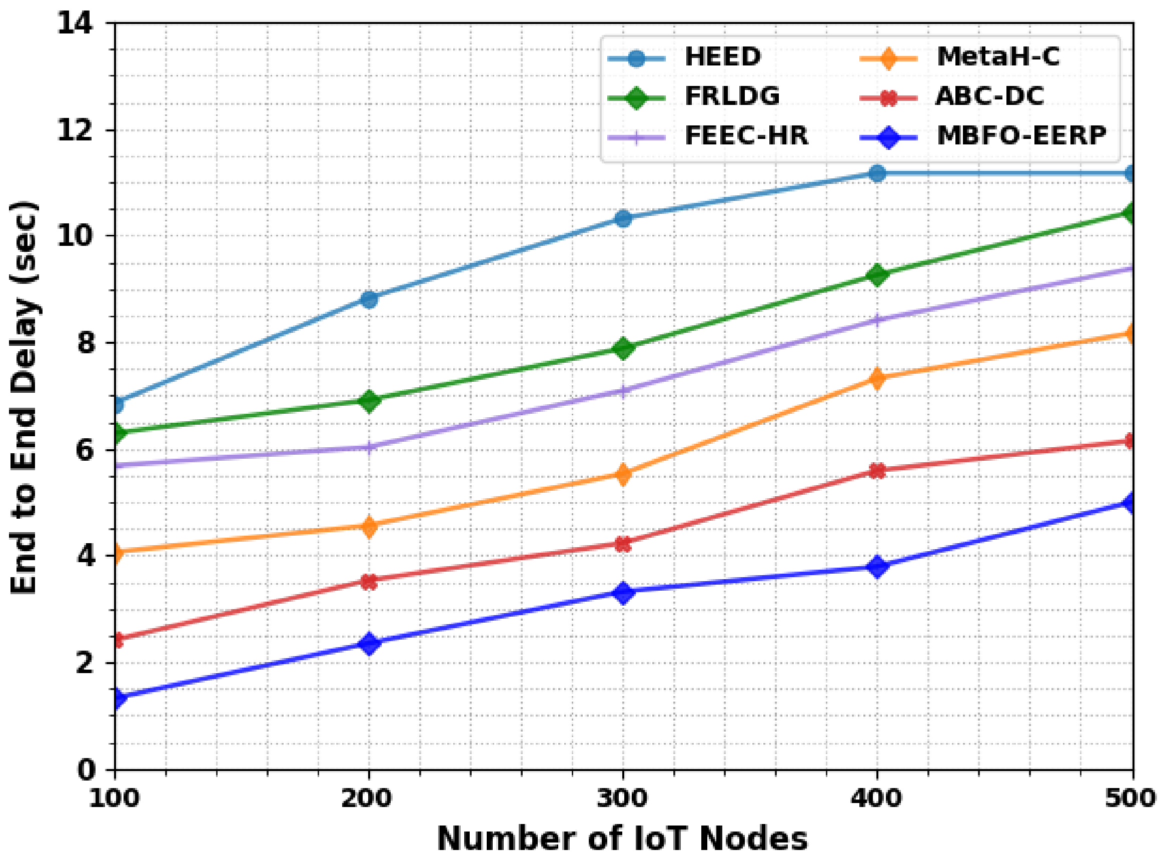

Fig. 7. ETED analysis of MBFO-EERP approach under varying IoT nodes

The detailed THRO investigation of the MBFO-EERP approach with current devices in Table 6 and Fig. 8. The outcomes show the MBFO-EERP method gain increased values of THRO under all nodes. For example, with 100 IoT nodes, the MBFO-EERP method accomplish improvising THRO of 0.9655Mbps while the HEED, FRLDG, FEEC-HR, MetaH-C, and ABC-DC techniques reach decreased THRO of 0.6155Mbps, 0.7358Mbps, 0.7949Mbps, 0.8383Mbps, and 0.9408Mbps correspondingly. Furthermore, with 500 IoT nodes, the MBFO-EERP method accomplish improvising THRO of 0.8026Mbps while the HEED, FRLDG, FEEC-HR, MetaH-C, and ABC-DC systems reach decreased THRO of 0.4026Mbps, 0.4282Mbps, 0.5268Mbps, 0.6313Mbps, and 0.6648Mbps correspondingly.

Table 6 THRO analysis of MBFO-EERP approach with other systems under changing IoT nodes

Throughput (Mbps)						
Number of IoT Nodes	**HEED**	**FRLDG**	**FEEC-HR**	**MetaH-C**	**ABC-DC**	**MBFO-EERP**
100	0.6155	0.7358	0.7949	0.8383	0.9408	0.9655
200	0.6155	0.6845	0.7772	0.8304	0.9329	0.9755
300	0.5366	0.6214	0.6944	0.7180	0.8935	0.9366
400	0.4617	0.5209	0.5820	0.6293	0.7594	0.8461
500	0.4026	0.4282	0.5268	0.6313	0.6648	0.8026

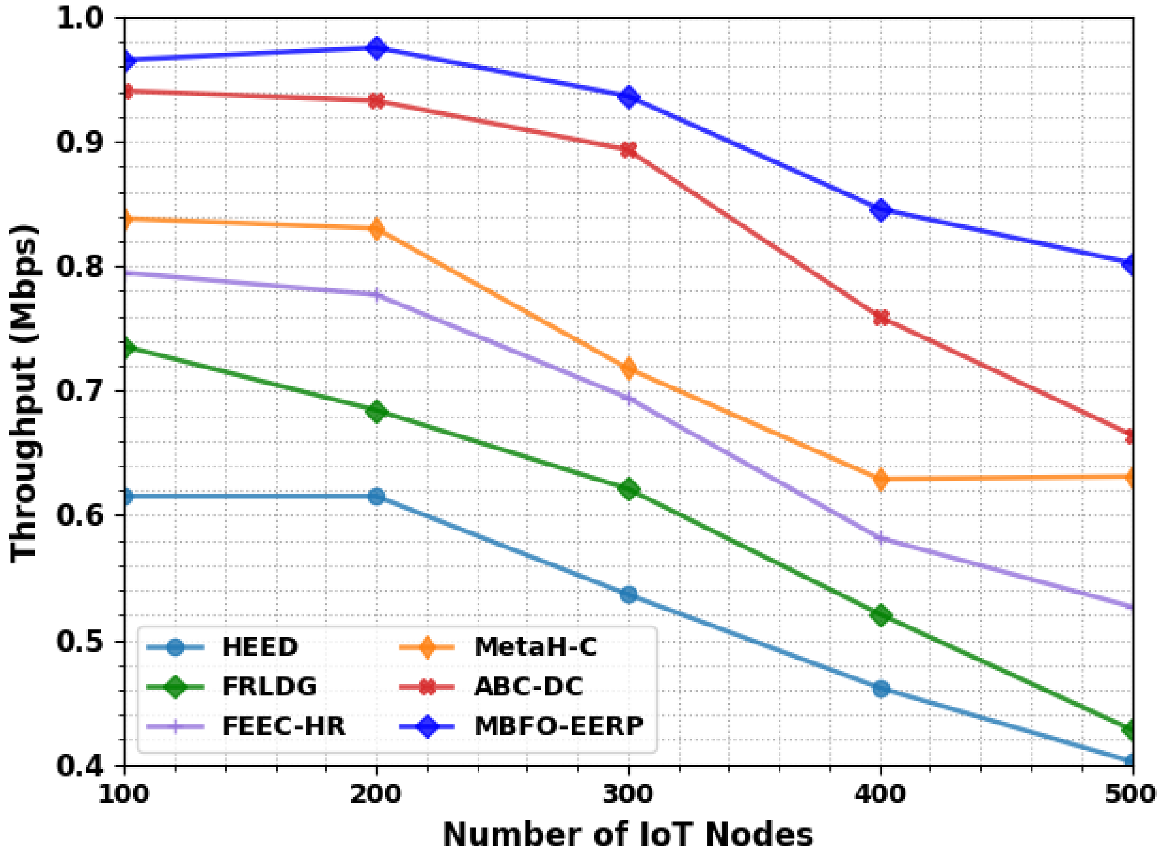

Fig. 8. THRO analysis of MBFO-EERP approach under varying IoT nodes

In Table 7 and Fig. 9, the detailed BER outcomes of the MBFO-EERP method are investigated with other existing models. The figure indicates that the MBFO-EERP system reaches improvised results over other models. For example, with 100 IoT nodes, the MBFO-EERP approach gains least BER of 9.43% while the HEED, FRLDG, FEEC-HR, MetaH-C, and ABC-DC models attain reducing BER of 26.92%, 24.58%, 22.89%, 19.16%, and 12.87% respectively. Simultaneously, with 500 IoT nodes, the MBFO-EERP technique obtains least BER of 2.62% while the HEED, FRLDG, FEEC-HR, MetaH-C, and ABC-DC models attain reducing BER of 16.38%, 10.01%, 8.04%, 6.13%, and 4.67% correspondingly.

Table 7 BER analysis of MBFO-EERP approach with other techniques under changing IoT nodes

Bit Error Rate (%)						
Number of IoT Nodes	**HEED**	**FRLDG**	**FEEC-HR**	**MetaH-C**	**ABC-DC**	**MBFO-EERP**
100	26.92	24.58	22.89	19.16	12.87	9.43
200	25.97	20.70	17.55	14.33	10.31	6.43
300	22.16	16.16	13.89	10.16	8.40	3.79
400	18.14	13.23	9.87	6.72	5.04	2.33
500	16.38	10.01	8.04	6.13	4.67	2.62

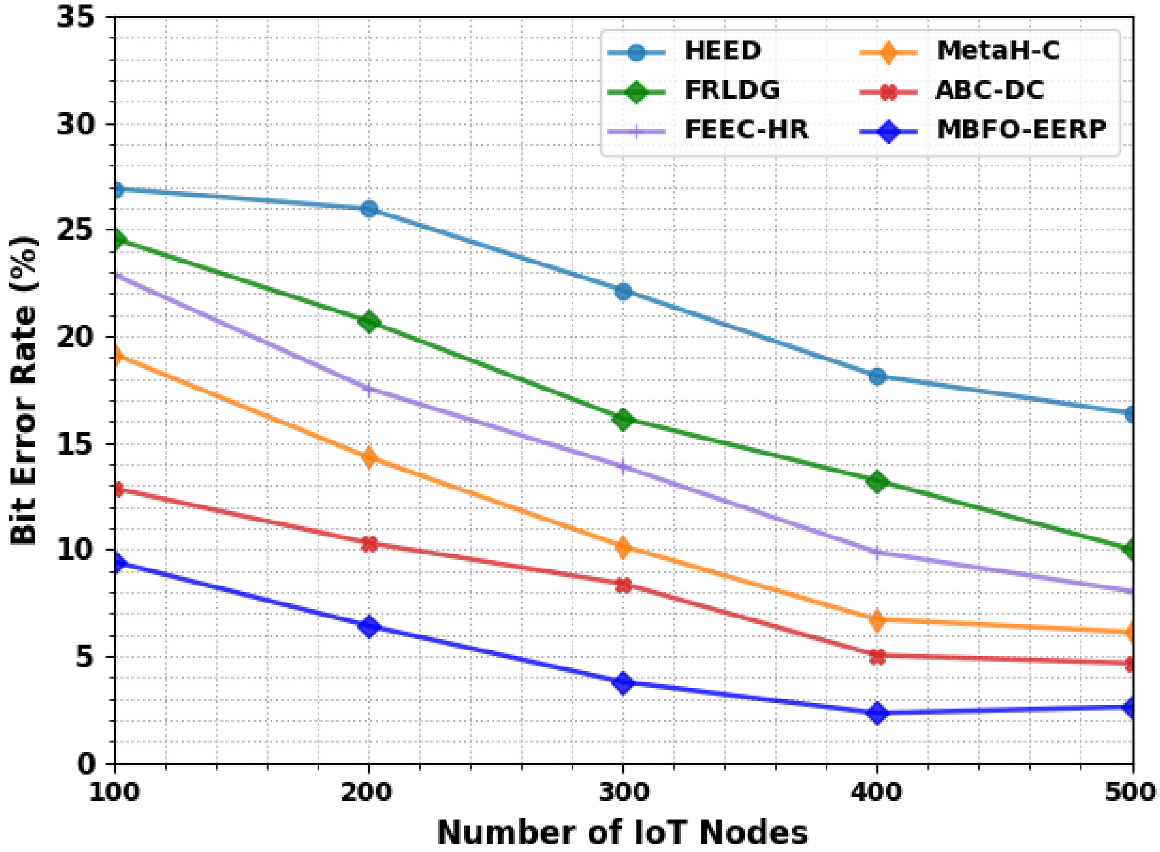

Fig. 9. BER analysis of MBFO-EERP method under changing IoT nodes

In Table 8 and Fig. 10, detailed jitter outcomes of the MBFO-EERP technique are investigated with other existing models. The experimental values signify that the MBFO-EERP technique reaches improvised results over other models. For instance, with 100 IoT nodes, the MBFO-EERP technique gains least jitter of 0.3348ms while the HEED, FRLDG, FEEC-HR, MetaH-C, and ABC-DC models attain reducing jitter of 0.6502ms, 0.6029ms, 0.5446ms, 0.4331ms, and 0.3918ms correspondingly.

Table 8 Jitter analysis of MBFO-EERP methodwith other approaches under changing IoT nodes

Jitter (ms)						
Number of IoT Nodes	**HEED**	**FRLDG**	**FEEC-HR**	**MetaH-C**	**ABC-DC**	**MBFO-EERP**
100	0.6502	0.6029	0.5446	0.4331	0.3918	0.3348
200	0.6502	0.5713	0.5459	0.4561	0.3712	0.3251
300	0.6405	0.5604	0.5216	0.4500	0.3603	0.3118
400	0.6198	0.5434	0.4925	0.4282	0.3445	0.2948
500	0.5895	0.5495	0.4573	0.4088	0.3482	0.2620

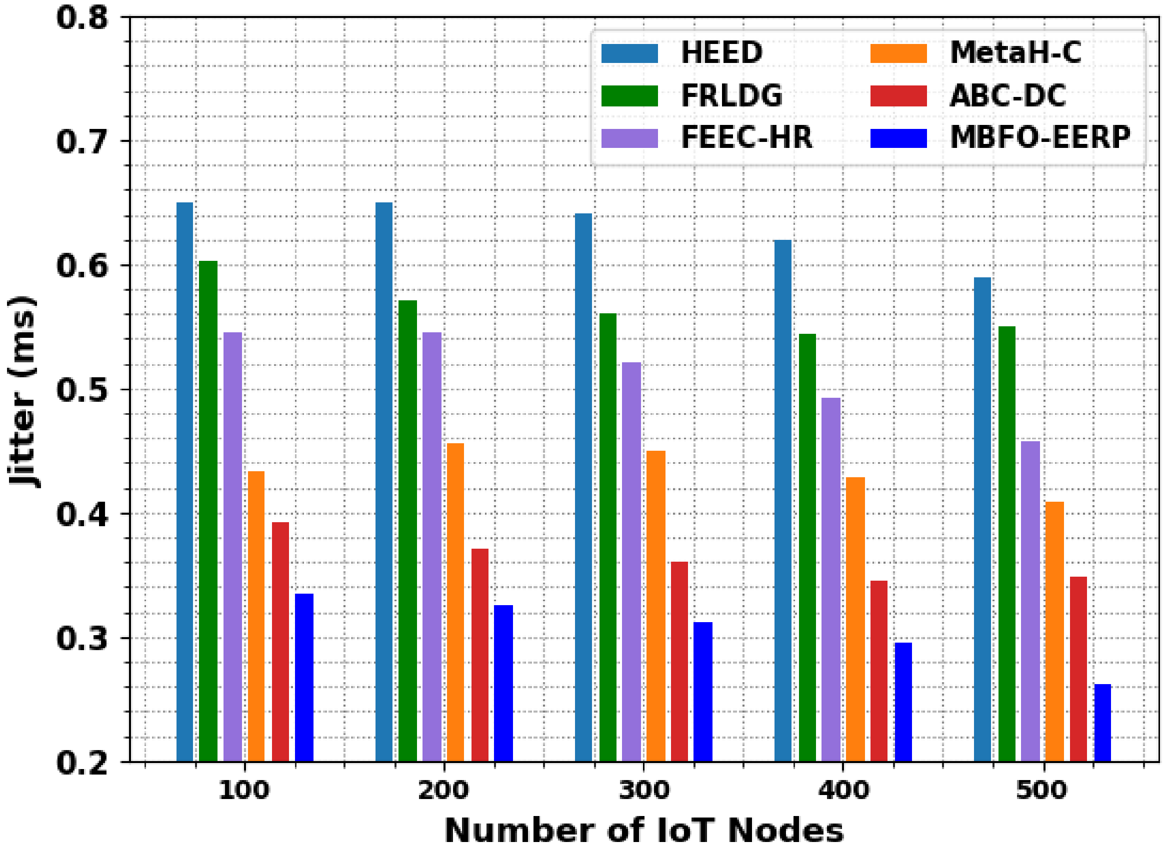

Fig. 10. Jitter analysis of MBFO-EERP approach under varying IoT nodes

Concurrently, with 500 IoT nodes, the MBFO-EERP approach gains least jitter of 0.2620ms while the HEED, FRLDG, FEEC-HR, MetaH-C, and ABC-DC models attain reducing jitter of 0.5895ms, 0.5495ms, 0.4573ms, 0.4088ms, and 0.3482ms respectively. Therefore, the proposed model accomplishes better performance over other models.

5. Conclusion

In this article, we have developed a new MBFO-EERP technique for selecting the optimal set of routes to destination in the IoT assisted WSN. To accomplish this, the MBFO-EERP technique followed the random node deployment and node initialization process. In addition, the presented MBFO-EERP technique integrated the concept of LF into the conventional BFO algorithm. Moreover, the fitness function of the MBFO-EERP technique integrates three input parameters such as intra-cluster distance, inter-cluster distance, and residual energy. To exhibit the enhanced efficacyof the MBFO-EERP method, a wide-ranging simulation analysis is performed. The extensive outcomes demonstrate the betterment of the MBFO-EERP technique over other measures. In future, the performance of the MBFO-EERP technique can be improvised by unequal clustering process.

References

[1] Nath, S. and Sarkar, S.K., 2021. Metaheuristics-based routing optimisation, balanced workload distribution and security strategy in IoT environment. *International Journal of Advanced Intelligence Paradigms*, *19*(1), pp.101-117.

[2] Nagappan, K., Rajendran, S. and Alotaibi, Y., 2022. Trust Aware Multi-Objective Metaheuristic Optimization Based Secure Route Planning Technique for Cluster Based IIoT Environment. *IEEE Access*, *10*, pp.112686-112694.

[3] Sankar, S., Ramasubbareddy, S., Chen, F. and Gandomi, A.H., 2020, December. Energy-efficient cluster-based routing protocol in internet of things using

swarm intelligence. In *2020 IEEE Symposium Series on Computational Intelligence (SSCI)* (pp. 219-224). IEEE.

[4] Rana, B., Singh, Y. and Singh, H., 2021. Metaheuristic Routing: A Taxonomy and Energy-Efficient Framework for Internet of Things. *IEEE Access*, *9*, pp.155673-155698.

[5] Ai, Z.Y., Zhou, Y.T. and Song, F., 2018. A smart collaborative routing protocol for reliable data diffusion in IoT scenarios. *Sensors*, *18*(6), p.1926.

[6] Senthil, G.A., Raaza, A. and Kumar, N., 2021. Internet of things multi hop energy efficient cluster-based routing using particle swarm optimization. *Wireless Networks*, *27*(8), pp.5207-5215.

[7] RahnamaeiYahiabadi, S., Barekatain, B. and Raahemifar, K., 2019. TIHOO: an enhanced hybrid routing protocol in vehicular ad-hoc networks. *EURASIP Journal on Wireless Communications and Networking*, *2019*(1), pp.1-19.

[8] Priyanka, P. and Kaur, J., 2018, June. Ant colony optimization based routing in IoT for healthcare services. In *2018 Second International Conference on Intelligent Computing and Control Systems (ICICCS)* (pp. 1155-1159). IEEE.

[9] Grosso, J. and Jhumka, A., 2021, November. Fault-Tolerant Ant Colony Based-Routing in Many-to-Many IoT Sensor Networks. In *2021 IEEE 20th International Symposium on Network Computing and Applications (NCA)* (pp. 1-10). IEEE.

[10] Jainulabudeen, A. and Surputheen, M.M., 2022. Novel Two-Level Randomized Sector-based Routing to Maintain Source Location Privacy in WSN for IoT. *IJCSNS*, *22*(3), p.285.

[11] Seyfollahi, A., Taami, T. and Ghaffari, A., 2023. Towards developing a machine learning-metaheuristic-enhanced energy-sensitive routing framework for the internet of things. *Microprocessors and Microsystems*, *96*, p.104747.

[12] Lakshmanna, K., Subramani, N., Alotaibi, Y., Alghamdi, S., Khalafand, O.I. and Nanda, A.K., 2022. Improved metaheuristic-driven energy-aware cluster-based routing scheme for IoT-assisted wireless sensor networks. *Sustainability*, *14*(13), p.7712.

[13] Revanesh, M. and Sridhar, V., 2021. A trusted distributed routing scheme for wireless sensor networks using blockchain and meta-heuristics-based deep learning technique. *Transactions on Emerging Telecommunications Technologies*, *32*(9), p.e4259.

[14] Gali, S. and Nidumolu, V., 2022. An intelligent trust sensing scheme with metaheuristic based secure routing protocol for Internet of Things. *Cluster Computing*, *25*(3), pp.1779-1789.

[15] Cano, J.A., Cortés, P., Muñuzuri, J. and Correa-Espinal, A., 2022. Solving the picker routing problem in multi-block high-level storage systems using metaheuristics. *Flexible Services and Manufacturing Journal*, pp.1-40.

[16] Mir, M., Yaghoobi, M. and Khairabadi, M., 2022. A new approach to energy-aware routing in the Internet of Things using improved Grasshopper Metaheuristic Algorithm with Chaos theory and Fuzzy Logic. *Multimedia Tools and Applications*, pp.1-27.

[17] Praveen, K.V. and Prathap, P.M., 2021. Energy Efficient Congestion Aware Resource Allocation and Routing Protocol for IoT Network using Hybrid Optimization Techniques. *Wireless Personal Communications*, *117*(2), pp.1187-1207.

[18] Yousefi, S., Derakhshan, F., Aghdasi, H.S. and Karimipour, H., 2020. An energy-efficient artificial bee colony-based clustering in the internet of things. *Computers & Electrical Engineering*, *86*, p.106733.

[19] D Saravanan, J Feroskhan, R Parthiban, S Usharani, "Secure Violent Detection in Android Application with Trust Analysis in Google Play", *Journal of Physics: Conference Series* 1717 (1), 012055.

[20] D Saravanan, E Racheal Anni Perianayaki, R Pavithra, R Parthiban, " Barcode System for Hotel Food Order

with Delivery Robot", *Journal of Physics: Conference Series* 1717 (1), 012054.

[21] D Raghu Raman, S Gowsalya Devi, D Saravanan, "Locality based violation vigilant system using mobile application", *2020 International Conference on System, Computation, Automation and Networking* (ICSCAN-IEEE).

[22] R Parthiban, R Ezhilarasi, D Saravanan, "Optical Character Recognition for English Handwritten Text Using Recurrent Neural Network", *2020 International Conference on System, Computation, Automation and Networking* (ICSCAN-IEEE).

[23] R Parthiban, V Abarna, M Banupriya, S Keerthana, D Saravanan," Web Folder Phishing Discovery and Prevention with Customer Image Verification", *2020 International Conference on System, Computation, Automation and Networking* (ICSCAN-IEEE).

[24] Mortazavi, A. and Moloodpoor, M., 2021. Enhanced butterfly optimization algorithm with a new fuzzy regulator strategy and virtual butterfly concept. *Knowledge-Based Systems*, *228*, p.107291.

[25] Nabavi, S.R., OsatiEraghi, N. and Akbari Torkestani, J., 2022. Intelligent Optimization of QoS in Wireless Sensor Networks Using Multiobjective Grey Wolf Optimization Algorithm. *Wireless Communications and Mobile Computing*, *2022*.

[26] Preeth, S.K., Dhanalakshmi, R., Kumar, R. and Shakeel, P.M., 2018. An adaptive fuzzy rule based energy efficient clustering and immune-inspired routing protocol for WSN-assisted IoT system. *Journal of Ambient Intelligence and Humanized Computing*, pp.1-13.