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An Energy-Efficient Quantum Sunflower Optimization Based Clustering Algorithm for Internet of Things Environment

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Abstract

Internet of Things (IoT) is a network of Internet enabled gadgets which has the ability of sensing, communicating, and reacting to the changes occurred in the target region. It finds use in several application areas ranging from civilian to military application. The collaboration amongst the IoT gadgets in several applications in the real time environment poses a challenging issue. In addition, energy constrained characteristics of the IoT devices also encounters a major design issue and can be resolved by the use of clustering techniques. This paper presents an energy-efficient quantum sunflower optimization based clustering (EEQSFOC) technique for IoT environments. The sunflower optimization (SFO) algorithm is based on the movement of sunflowers to observe solar radiations. In addition, quantum computing concept is incorporated into the SFO algorithm to improve the searching process, and obtain better tradeoff among the exploration and exploitation capabilities. For validating the effectual energy efficient performance of the EEQSFOC technique, a set of simulations were performed and the results are examined interms of distinct measures. The experimental outcome ensured the betterment of the EEQSFOC technique over the existing clustering techniques.

Keywords: Internet of Things, Energy Efficiency, Clustering, Quantum computing, Metaheuristics

1. Introduction

The achievement of wireless sensor networks (WSN) about the technologies as well as applications in various domains such as industrial applications, home automation, military surveillance, and safety, etc increases the additional requirement for machine to machine connectivity and accessibility of the information (or) data ubiquitously [1]. This necessity results in the design of Internet of Things (IoT). IoT enables the connectivity between the devices as well as benefits in collection of information or data at any place and any time. Therefore, many applications are coming up for IoT by the use of different technologies [2]. Likewise, IoT allows advanced services in many applications related to smart homes, smart transportation, smart lifestyle, smart cities, smart industries, smart healthcare, etc.[3,4]. The uses of these applications and the need have been raised the research scope and the innovation of these domains [5].

An important part of above-mentioned application areas by means of IoT requests sensing and observing the environment or collecting the information from diverse IP enabled sensors or devices. The sensor devices are utilized to sense and monitor the environment are energy constrained and battery-operated. It suggests that energy and power utilization are crucial. IP based communication effectively uses additional energy that results in low powered devices for rapid energy depletion. It increases the requirement for efficient

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connectivity and effective communication between the devices optimally is a challenging process. Therefore, a solution is required to achieve higher connectivity with minimal data transmission [6]. An effective way to satisfy the particular requirements to collaborate between the sensors or devices and carry out the processes for a specific application. Fig. 1 shows the process of IoT.

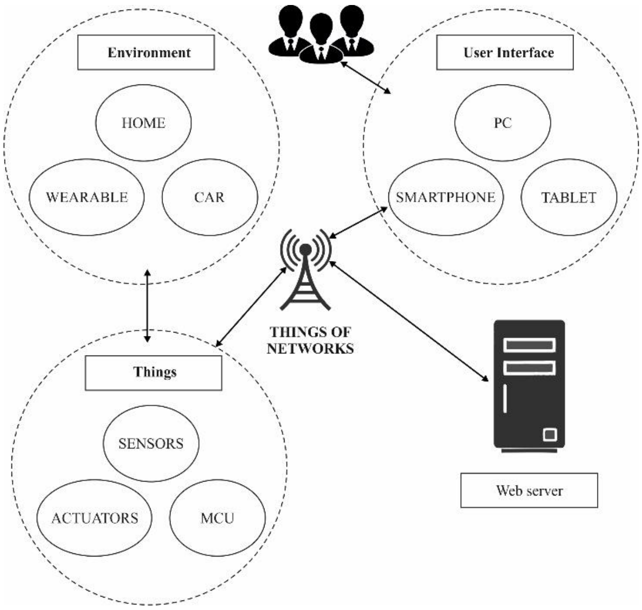

Fig. 1. A scenario of IoT

Clustering the devices is a proficient method of achieving less energy utilization and computation complexity. For any IoT based applications, it is needed to gather the information by sensing devices and processes the data using diverse techniques. Next, the processed data can be accessed ubiquitously. The clustering process refers to the grouping of devices or sensors. The clustering process assists to carry out to gather data effectively with minimal communication in the network and disseminates the data for additional processing. Clustering still assists in extending the network lifetime and additionally the lifetime of the application. In the IoT environment, the effectual clustering should require (1) Classifications among the original sensors and Internet protocols (IP) enabled systems (2) accessing the data with low minimum communication overhead. In clustering, individual cluster selects a node inside the cluster as a cluster head (CH), and more communication between the nodes in the network takes place using the CH. If two nodes in the network do not exist in the range of one another, multihop data transmission is required. Communication over CH avoids multi-hop data transmission to a certain range. The CH assists to aggregate the data collected by various nodes in the network. In the IoT based network, 2-layered model contains IoT and sensor layers. They are two ways of grouping these devices like from sensor layer IoT layer and vice versa.

This paper presents an energy-efficient quantum sunflower optimization based clustering (EEQSFOC) technique for IoT environments. The sunflower optimization (SFO) algorithm is based on the movement of sunflowers to observe solar radiations. In addition, quantum computing concept is combined with the SFO algorithm to expand the searching process, and attain better tradeoff among the exploration and exploitation capabilities. For confirming the capable energy efficient outcome of the EEQSFOC technique, a series of experimentations take place and the results are inspected interms of distinct measures. The experimental outcome ensured the betterment of the EEQSFOC technique over the existing clustering techniques.

In short, the paper contribution can be summarized as follows.

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- To introduce an energy efficient clustering technique named EEQSFOC for IoT environment.
- To employ quantum computing based SFO algorithm for CH selection and cluster construction process.
- To derive a fitness function using four measures namely energy, node degree, distance to neighboring IoT devices, and distance to BS.
- To a validate the performance of the EEQSFOC technique under varying number of IoT nodes.

The rest of the paper are organized as follows. Section 2 briefs the work related to the study. Section 3 introduces the presented EEQSFOC technique and detailed experimental validation is provided in section 4. Finally, section 5 concludes the study.

2. Related works

In the earlier studies, several works are detected to present the IoT architectures [7, 8] interms of generic architecture or reference method. They are developed by the theoretical stage with no experimentation and authentication. This method is more complicated for 1-to-1 mapping in all real-time applications. Previously, IoT architectures [9, 10] have been given in an intellectual manner and estimate the result. In this way, a 2-layered IoT architecture is developed and the data transmission cost might be decreased to one or almost 2-hops for any nodes in the network. As discussed before, the nodes are small as well as energy limited. In this environment, it is preferable to create the collection of devices also the set of devices can communicate between them through the group leader which verifies the minimal data transmission overhead also the energy efficient operation by the use of clustering.

Presently, the sensor nodes in clustering are addressed in the IoT platform. The considerable facts related to the differences between the clustering in WSN and the IoT techniques are essential to be distinguished. In WSN, clustering in the network takes place in a local way, while clustering in IoT can be always examined in a global way in the network. The node connectivity and density are the limited parameters involved in the WSN whether they are with or without layered, and also, they are more controlled over the mobile nature of the nodes. However, the number of nodes cannot be controlled in the IoT environment. In addition, the mobile nature of IoT node enables on-the-fly clustering by underlying the sensor nodes in a dynamic way in the target region, that is impossible in WSN.

Moreover, in the prior works, none of the clustering methods are designed specifically for IoT platforms. The 2 layered architecture in the IoT has been made in the previous works. In Lloret et al. [11], the clustering based framework is introduced the arrange the topology in various WSN to exist along with a similar platform through the formation of the virtual WSN. Correspondingly, the layered based clustering method has been described for routing the homogeneous and densely placed network with cross layered communication. The method is cannot support the detection of nodes on-the-fly that is required for the network with mobility that allows accessing of data at any place and any time. In the presented model, there are no constraints for densely connected network arrangement which is related to this model in [12]. Furthermore, it also supports the clustering technique in heterogeneous networks.

3. The Proposed EEQSFOC Technique

The working principle involved in the presented EEQSFOC technique is illustrated in Fig. 2. As depicted in the figure, the IoT devices are deployed arbitrarily in the target region. Then, the IoT devices gather details about the neighboring IoT devices. Afterward, the EEQSFOC algorithm gets executed to elect an optimum set

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of (CHs). Afterward, the elected CHs broadcast advertisements to construct clustering by the joining of nearby IoT devices as cluster members (CMs).

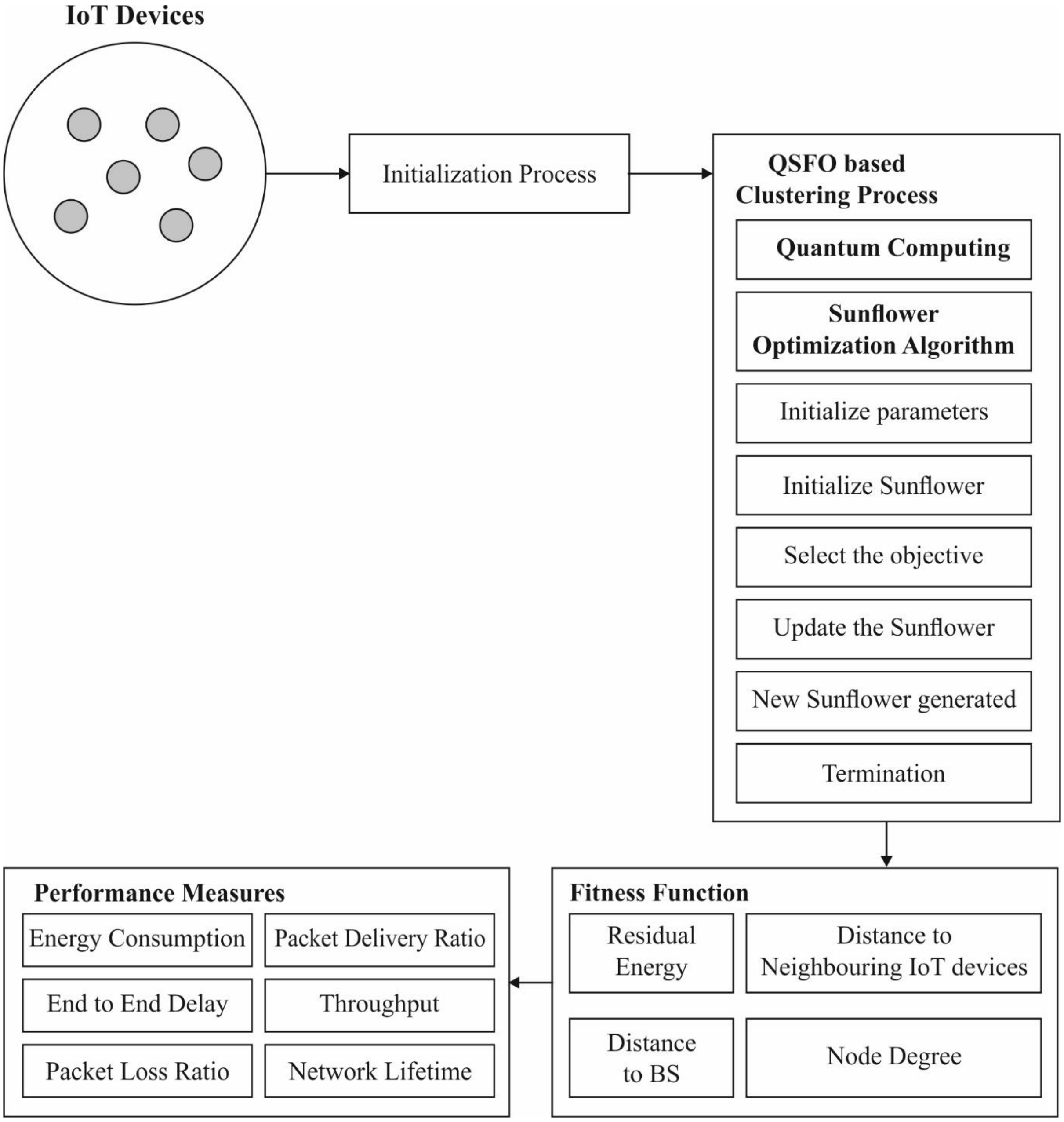

Fig. 2. Working process of EEQSFOC model

3.1. Overview of SFO algorithm

SFO is a population-based optimization algorithm commonly used to solve multi-dimensional problems. The concept of SFO algorithm is based on the movement of sunflowers for capturing solar radiation. The sunflower's cycle remains constant. On every single data, they wake up and go with the sun as same as the needle of a clock. During nighttime, it travels in the opposite direction for waitingover for their departure the succeeding morning.

Yang [13] presented a novel technique depending upon the flower pollination procedure of flowering plants seeing the biological procedure of reproduction. Here, the researchers have considered the particular

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characteristics of sunflowers in the search for optimal alignment with the sun. The pollination measured here was takenarbitrarily along with theleast distance among the flowers$i$and $\mathrm{i}+1$. Under real-time circumstances, the flower patches adequately release millions of pollen gametes. But, for research purposes, it is considered that every individual sunflower only generates one pollen gamete and replicatesseparately.

Another essential naturebased optimization algorithm is the inverse square law radiation. A law defines that the intensity of radiation is inversely proportional to the square of the distance, i.e., the intensity (quantity) of radiation gets reduced in a proportion to the square of the rise in distance. When the distance gets doubled, the intensity gets reduced to a factor 4, triples, lessens to a factor 9, etc. At this point, when the distance between the plant to sun is low, higher quantity of radiation gets absorbed and it tends to stabilize in these vicinities. In contrastingly, when the distance from the plant to sun is high, the quantity of radiation received will be low. Therefore, this concept is utilized here where the higher steps are needed to attain the global optima (sun).

At that time, the quantity of heat Qabsorbed by every individual plant can be defined as:

$$Q_i = \frac{P}{4\pi r_i^2}, \tag{1}$$

where$P$indicates the power of source and r_i the distance among the present best and plant i.An orientation of sunflower towards the sun can be represented as

$$\vec{s_i} = \frac{X^* - X_i}{||X * -X_i||}, i = 1, 2, \dots, n_p. \tag{2}$$

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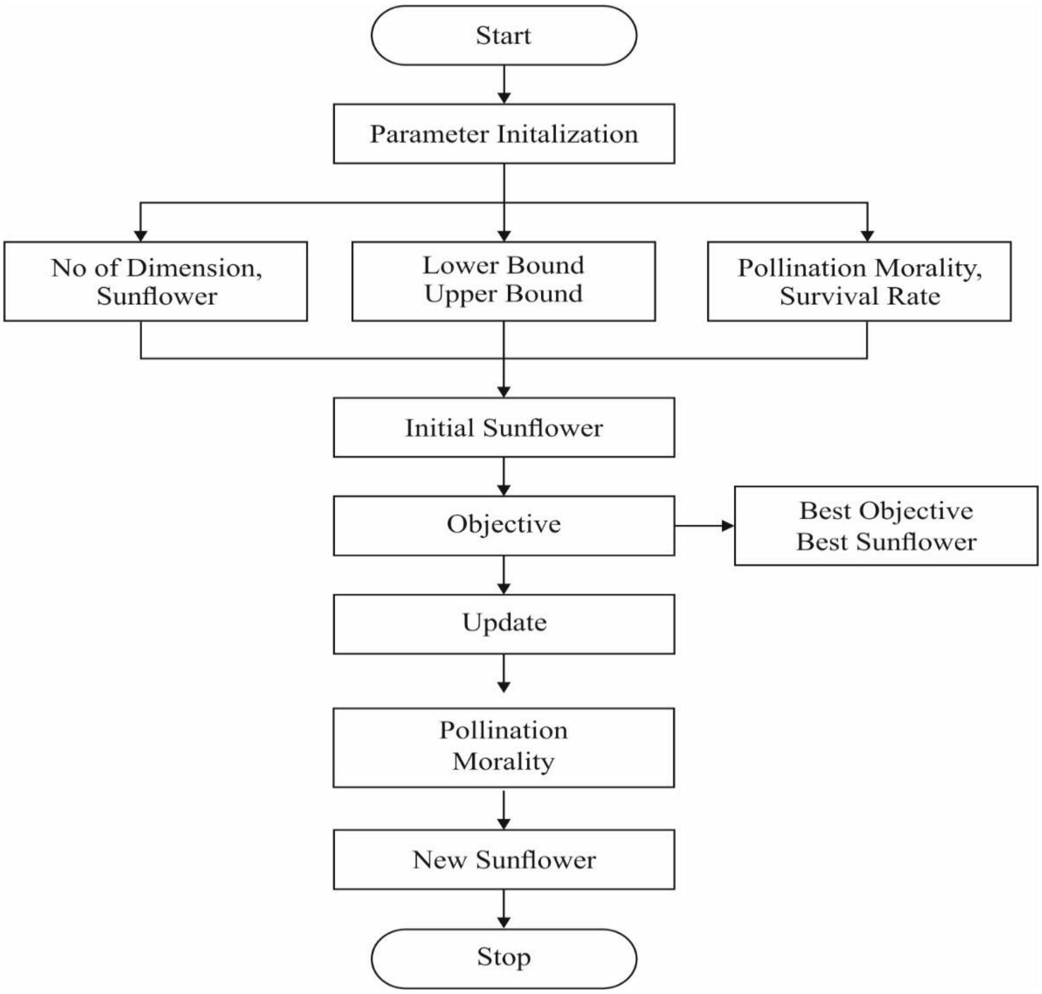

Fig. 3. Flowchart of SFO algorithm

The sunflower's on the direction $s$can be determined as

$$d_i = \lambda \times P_i(||X_i + X_{i-1}||) \times ||X_i + X_{i-1}||, \tag{3}$$

where λ is the constant defining the "inertial" displacement of the plant, $P_i(||X_i + X_{i-1}||)$ is the likelihood of pollination, i.e, the sunflower $i$cross-pollinatesto the closer neighbor $i-1$producing a fresh individual in anarbitrary position which gets varied based on every distance amongst the flowers [14]. Therefore, the individuals nearer to the sun takes small steps in the searching process of a local refinement while higher distance individuals have normal movement. It is essential to limit the highest step provided by all the individuals to skip regions inclined tobe global minima candidates. Therefore, the maxima step can be determined by:

$$d_{\max} = \frac{||X_{\max} - X_{\min}||}{2 \times N_{\text{pop}}}, \tag{4}$$

where$X_{\max}$ and $X_{\min}$ are the upper and lower boundaries and N_{pop}plant count in total population. Then, the fresh plantation can be represented as:

$$\vec{X}_{t+1} = \vec{X}_i + d_i \times \vec{s_i}. \tag{5}$$

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The SFO algorithm starts with the creation of population in an arbitrary or uniform way. Then, the validation of all the individuals enables evaluations where one is converted into the sun, that is, the one with the optimal evaluation amongst everyone. Fig. 3 demonstrates the flowchart of SFO technique.

3.2. Design of QSFO Algorithm

For complete exploration of the search space, every quantum sunflower is considered as an independent individual, and lastly, the approximated global best solutions are obtained by undergoing a comparison of the local optimum solution with the individuals. Quantum computing is a new kind of computing system that implements the quantum theory namely state superposition, quantum entanglement, and quantum measurement. A fundamental unit of quantum computing is qubit [15]. It has 2 simple states namely $|0>$ and $|1>$ procedure a qubit that is illustrated as a linear combination of these 2 simple forms as under:

$$|Q>=\alpha|0>+\beta|1>. \tag{6}$$

$|\alpha|^2$implies the possibility of observed form $|0>$, $|\beta|^2$ refers the possibility of observed form $|1>$, where $|\alpha|^2+|\beta|^2=1$. The quantum is developed to n qubits. Because of the nature of quantum superposition, all the quantahave of 2^n feasible values. The n-qubits quantum is represented as follows:

$$\Psi=\sum_{x=0}^{2^n-1} C_x\,|x>,\sum_{x=0}^{2^n-1}|C_x|^2=1. \tag{7}$$

The quantum gates are modified in the form of qubits like NOT gate,rotation gate,Hadamard gate, etc. The rotation gate is explained as mutation operator for making quanta method optimal solutions and eventually determine the global optimal solution [16]. The rotation gate is determined as:

$$\begin{bmatrix}\alpha^d(t+1)\\ \beta^d(t+1)\end{bmatrix}=\begin{bmatrix}\cos(\triangle\theta^d) & -sin(\triangle\theta^d)\\ sin(\triangle\theta^d) & cos(\triangle\theta^d)\end{bmatrix}\begin{bmatrix}\alpha^d(t)\\ \beta^d(t)\end{bmatrix} for\ d=1,2,\dots,n. \tag{8}$$

$\triangle\theta^d=\triangle\times S(\alpha^d,\beta^d)$, $\triangle\theta^d$ denotes the rotation angle of qubit, where $\triangle$ and $S(\alpha^d,\beta^d)$ are size as well as direction of rotation correspondingly.

3.3. Application of QSFO algorithm for energy efficient clustering

Here, the QSFO algorithm is executed to develop clustering process using 4 variables namely energy, distance between nodes, node density, and distance to BS.The fitness function (FF) involved in the EEQSFOC technique is discussed below.

1) **Residual energy (RE):** Since the CHs are required to carry out distinct processes like sense, gather, aggregate, and transmit data, it leads to faster energy depletion over the other ones. Therefore, it is needed to compute a FFwhich distributes the load between the IoT nodes in the network. The fitness parameter to the realenergy utilization can be defined as follows.

$$R_e=e(n_i),Avg_e=\frac{1}{n}\sum_{i=0}^{n}e(n_i) \tag{9}$$

$$f_1=CH_{opt}*\frac{R_e}{Avg_e}=\frac{CH_{opt}*e(n_i)}{\frac{1}{n}\Sigma_{i=0}^{n}e(n_i)}\forall CH_{opt}$$

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$$= 5\%\, of n, e(n_i) = 0.5J or\ 1.25J or\ 1.75J \tag{10}$$

where, R_e, Avg_e, and n_i are node remaining energy, network average energy, and total node count. $CH_{opt}$is the optimal number of CHs. The objective function $f_1$defines the ratio of RE of individual nodes to the average energy of the network.

2) **Node density:**Duringintracluster communication, cost is considered a major variable used to increase the energy efficiency of the network. The higher node counts in the sequence of CHs make use of energy management in the network, or else network energy consumptionexceeds the cost function of cluster which can be computed as follows:

$$f_2 = \max\left(n(CH_1), n(CH_2), n(CH_3) n\left(CH_j\right)\right) \forall n = 2\ To\ 95, j = 1\ to\ 15 \tag{11}$$

where$n(CH_j)$denotes the IoT node count of j^{th} CH (CH_j). The objective function $f_2$is effective over the effectual selection of CHs and employs it to reduce energy exhaustion.

3) **Distance to neighboring IoT devices:** Duringintracluster communication, IoT nodes transmitted data to the CH. IF the CHs are far away from the CMs, it necessitates depletion of maximum energy when CH is closer to the CMs next to the utilization of least amount of energy.

$$f_3 = \frac{1}{n_{s\tau}} \sum_{i=0}^{n_{sr}} d\, isT(CH, i)\ \forall dist(CH, i) = 1\ to\ 35\ m, n_{sr} = 1\ to\ 100 \tag{12}$$

where, n_{sr} and $dist(CH, i)$denotes the IoT node count in the coverage area and Euclidean distance among the IoT nodes in a cluster. Therefore, the value of $f_3$needs to be low to reduce the intra cluster data transmission energy.

4) **Distance between CHs BS:**In the process of electing the CHs, the distance between the CHs and BS requires an essential process and it requires less distance between CHs and BS. It can be presented as:

$$f_4 = \frac{1}{CH} \sum_{\mathrm{i}=0}^{\mathrm{CH}} d\, ist(BS, CH_i)\ \forall dist(BS, CH_i) \tag{13}$$

where, $dist(BS, CH_i)$ is the Euclidean distance among BS andCH_i). The value off_4 objective function needs to be low.

When the objective functionsf_1, f_2, f_3, and $f_4$are determined, the objective function is named FF that can be defined as follows.

$$F = MaximizeFitness\ = \alpha * f_1 + \beta * f_2 + \gamma * \frac{1}{f_3} + \delta * \frac{1}{f_4} \tag{14}$$

where, α, β, γ, and δ are the weighted coefficients to f_1, f_2, f_3, and f_4 FF variables, respectively. The weighted coefficients range between 0 to 1.

4. Performance Validation

The performance of the proposed EEQSFOC technique is validated interms of different aspects. The parameter setting is given in Table 1.

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Table 1 Parameter Settings

Parameters	**Value**
Area	1000×1000m
Number of IoT devices	1000
Initial energy	0.1J
Bandwidth	20 kbps
Packet size	500 bytes
Node distribution	Random
Total number of nodes in the region	500
Antenna direction	Omni-directional

Table 2 investigates the brief comparative results analysis of the EEQSFOC algorithm with other existing algorithms interms of distinct measures [17, 18]. Fig. 4 showcases the results analysis of the EEQSFOC technique with other techniques interms of EC. The figure demonstrated that the EEQSFOC technique has showcased effective outcomes under all varying IoT nodes. For instance, under the existence of 100 IoT nodes, the EEQSFOC technique has achieved minimum EC of 36mJ whereas the FEEC-IIR, AFSAC, FUCHAR, and NFRCF-RP algorithms have obtained a maximum EC of 40mJ, 44mJ, 45mJ, and 57mJ respectively. Likewise, under the existence of 300 IoT nodes, the EEQSFOC model has reached lower EC of 74mJ whereas the FEEC-IIR, AFSAC, FUCHAR, and NFRCF-RP techniques have attained a higher EC of 91mJ, 93mJ, 97mJ, and 109mJ correspondingly. Simultaneously, under the existence of 500 IoT nodes, the EEQSFOC technique has achieved minimum EC of 107mJ whereas the FEEC-IIR, AFSAC, FUCHAR, and NFRCF-RP approaches have reached a superior EC of 132mJ, 136mJ, 145mJ, and 167mJ respectively.

Table 2 Result Analysis of Existing with Proposed EEQSFOC Method in terms of Various Measures

No. of IoT Nodes	**EC (mJ)**				
	EEQSFOC	**FEEC-IIR**	**AFSAC**	**FUCHAR**	**NFRCF-RP**
100	36	40	44	45	57
200	58	65	69	70	82
300	74	91	93	97	109
400	83	105	108	110	142
500	107	132	136	145	167
No. of IoT Nodes	**NL (Rounds)**				
	EEQSFOC	**FEEC-IIR**	**AFSAC**	**FUCHAR**	**NFRCF-RP**
100	5950	5570	5630	5030	5000
200	5870	5250	5450	4850	4700
300	5640	5050	5220	4730	4600
400	5430	4930	5160	4310	4290
500	5220	4760	4970	4150	4130
No. of IoT Nodes	**Packet Delivery Ratio (%)**				

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	EEQSFOC	FEEC-IIR	AFSAC	FUCHAR	NFRCF-RP
100	98	96	95	94	93
200	98	95	94	93	92
300	97	94	93	92	92
400	97	95	92	91	91
500	96	94	92	91	90
No. of IoT Nodes	**End to End Delay (sec)**				
	EEQSFOC	**FEEC-IIR**	**AFSAC**	**FUCHAR**	**NFRCF-RP**
100	2.30	2.60	2.95	3.15	3.30
200	2.45	4.10	3.70	3.90	4.20
300	2.56	5.20	4.40	4.60	4.90
400	3.43	6.00	5.60	5.70	6.20
500	5.21	6.60	6.80	7.00	7.20
No. of IoT Nodes	**Throughput (Mbps)**				
	EEQSFOC	**FEEC-IIR**	**AFSAC**	**FUCHAR**	**NFRCF-RP**
100	0.98	0.94	0.93	0.92	0.90
200	0.96	0.81	0.78	0.73	0.71
300	0.90	0.72	0.70	0.68	0.65
400	0.84	0.64	0.68	0.63	0.59
500	0.82	0.60	0.58	0.54	0.52
No. of IoT Nodes	**Packet Loss Ratio (%)**				
	EEQSFOC	**FEEC-IIR**	**AFSAC**	**FUCHAR**	**NFRCF-RP**
100	2	4	5	6	7
200	2	5	6	7	8
300	3	6	7	8	8
400	3	5	8	9	9
500	4	6	8	9	10

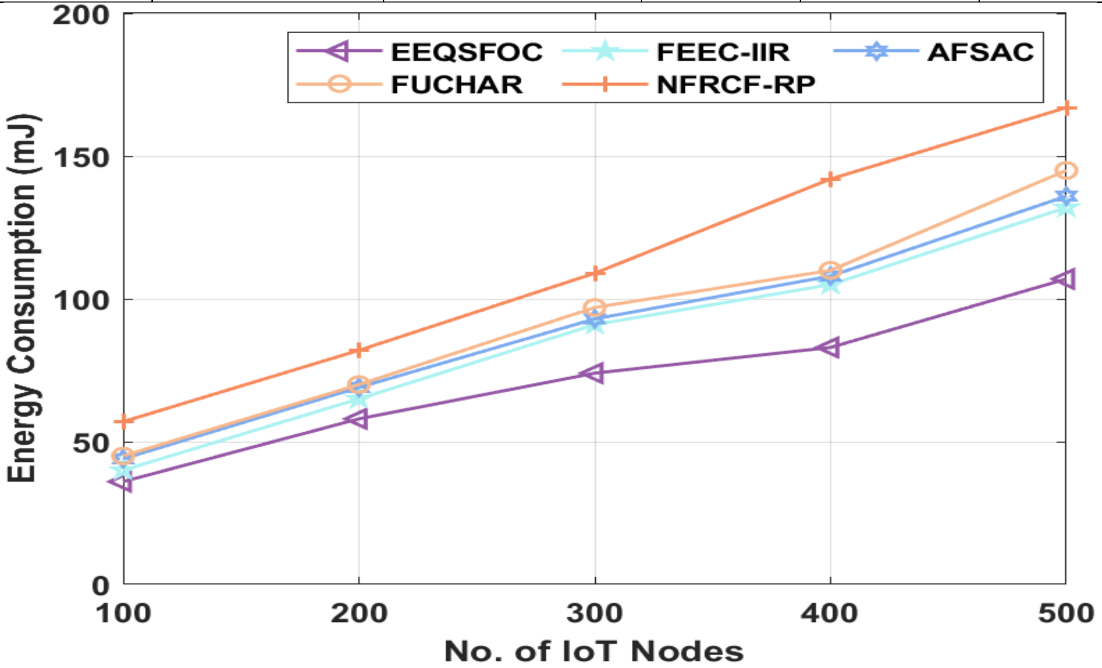

Fig. 4. EC analysis of the EEQSFOC technique with compared methods

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Fig. 5 provides a detailed NL analysis of the EEQSFOC technique with other existing methods under distinct IoT nodes. From the figure, it is obvious that the EEQSFOC technique has resulted in ineffective performance by accomplishing a higher NL. For instance, on the existence of 100 IoT nodes, the EEQSFOC technique has depicted an improved NL of 5950 rounds whereas the FEEC-IIR, AFSAC, FUCHAR, and NFRCF-RP techniques have reached a reduced NL of 5570, 5630, 5030, and 5000 rounds. Alike, on the existence of 300 IoT nodes, the EEQSFOC model has showcased a maximum NL of 5640 rounds whereas the FEEC-IIR, AFSAC, FUCHAR, and NFRCF-RP methodologies have achieved a minimum NL of 5050, 5220, 4730, and 4600 rounds. Comparably, on the existence of 500 IoT nodes, the EEQSFOC technique has demonstrated a higher NL of 5220 rounds whereas the FEEC-IIR, AFSAC, FUCHAR, and NFRCF-RP algorithms have attained a lower NL of 4760, 4970, 4150, and 4130 rounds.

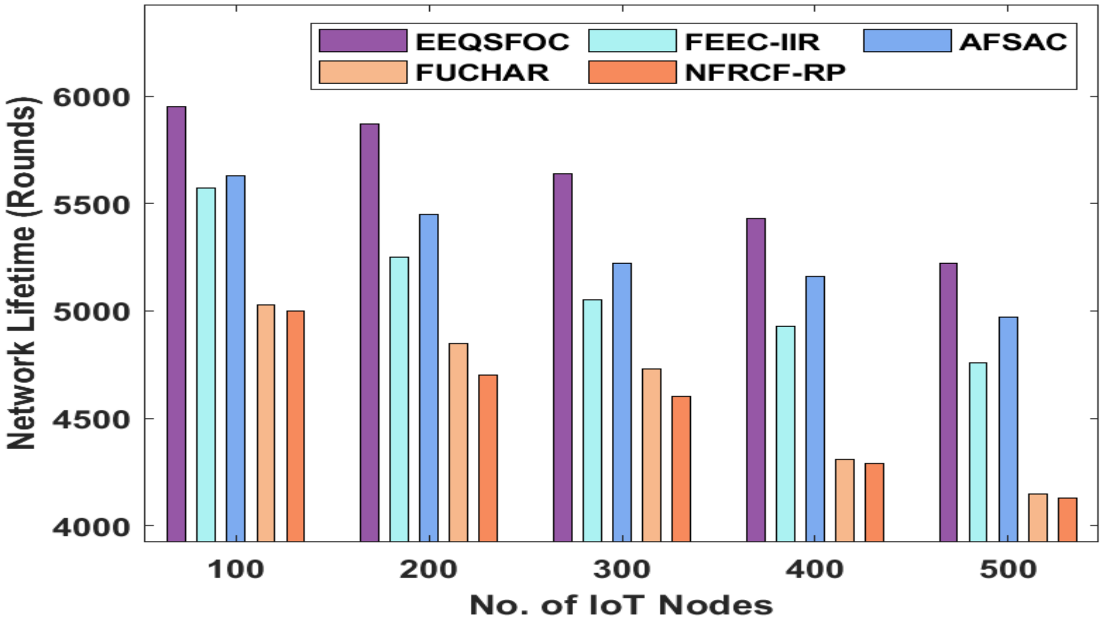

Fig. 5. NL analysis of the EEQSFOC technique with compared methods

Fig. 6 gives a detailed PDR analysis of the EEQSFOC method with other existing techniques under distinct IoT nodes. From the figure, it can be obvious that the EEQSFOC method has resulted in ineffective performance by accomplishing a maximum PDR. For instance, on the existence of 100 IoT nodes, the EEQSFOC model has exhibited a maximum PDR of 98% whereas the FEEC-IIR, AFSAC, FUCHAR, and NFRCF-RP methodologies have reached a reduced PDR of 96%, 95%, 94%, and 93%. In addition, on the existence of 300 IoT nodes, the EEQSFOC technique has portrayed a superior PDR of 97% whereas the FEEC-IIR, AFSAC, FUCHAR, and NFRCF-RP methods have reached a lesser PDR of 94%, 93%, 92%, and 92%. Also, on the existence of 500 IoT nodes, the EEQSFOC technique has depicted an improved PDR of 96% whereas the FEEC-IIR, AFSAC, FUCHAR, and NFRCF-RP techniques have attained a minimal PDR of 94%, 92%, 91%, and 90%.

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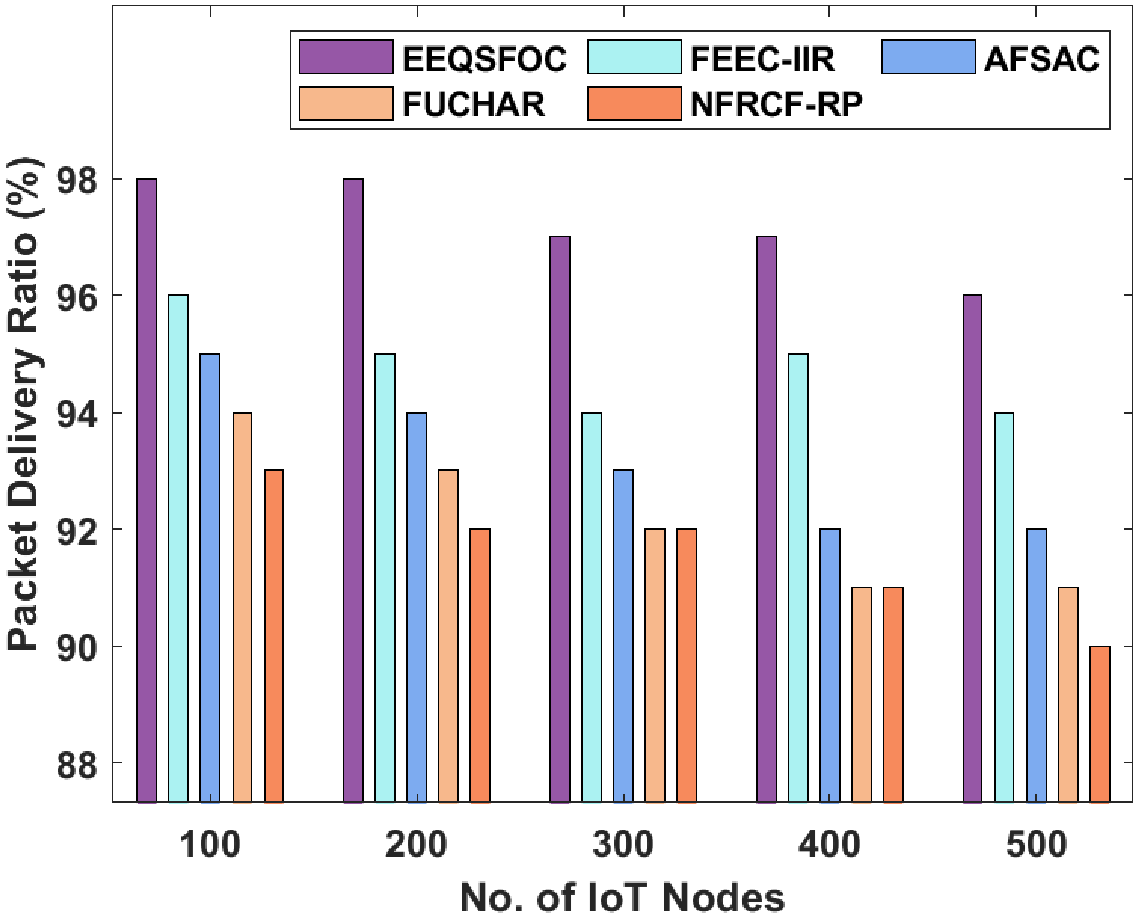

Fig. 6. PDR analysis of the EEQSFOC technique with compared methods

Fig. 7 demonstrates the outcomes analysis of the EEQSFOC model with other methods with respect to ETE delay. The figure showcased that the EEQSFOC technique has exhibited effective outcomes under all varying IoT nodes. For instance, under the existence of 100 IoT nodes, the EEQSFOC technique has reached minimal ETE delay of 2.30s whereas the FEEC-IIR, AFSAC, FUCHAR, and NFRCF-RP approaches have achieved a superior ETE delay of 2.60s, 2.95s, 3.15s, and 3.30s correspondingly. Besides, under the existence of 300 IoT nodes, the EEQSFOC model has attained lower ETE delay of 2.56s whereas the FEEC-IIR, AFSAC, FUCHAR, and NFRCF-RP models have obtained a maximum ETE delay of 5.20s, 4.40s, 4.60s, and 4.90s correspondingly. Moreover, under the existence of 500 IoT nodes, the EEQSFOC technique has achieved minimum ETE delay of 5.21s whereas the FEEC-IIR, AFSAC, FUCHAR, and NFRCF-RP approaches have attained a superior ETE delay of 6.60s, 6.80s, 7.0s, and 7.20s correspondingly.

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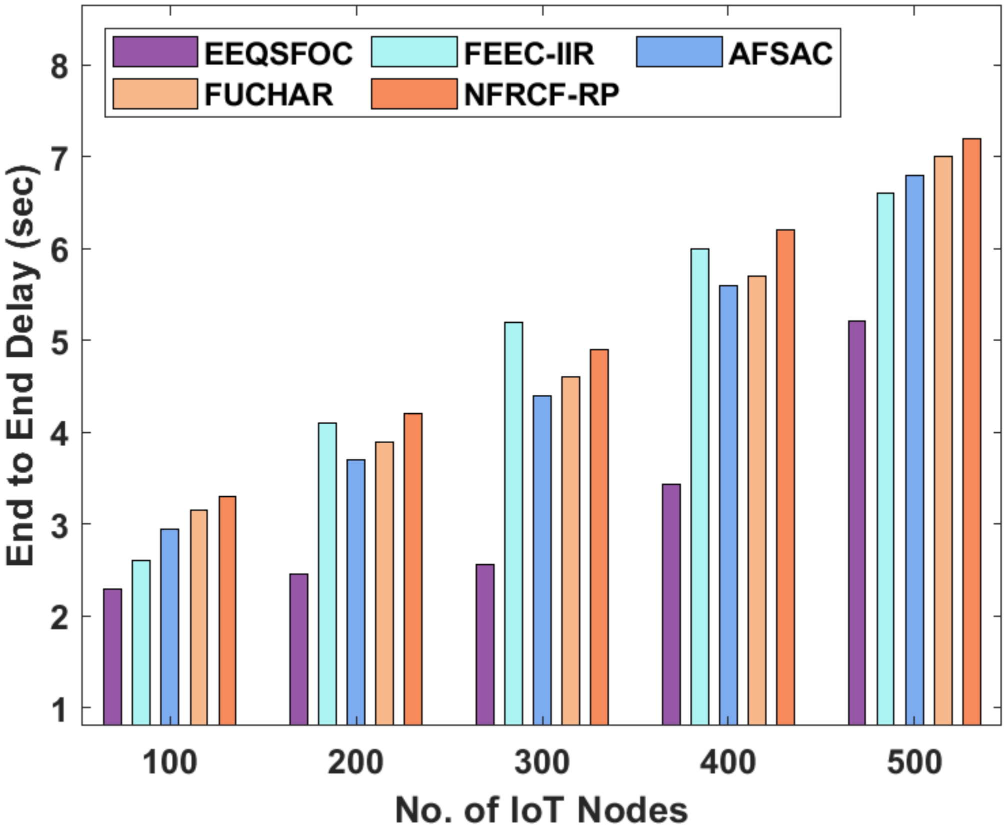

Fig. 7. ETE Delay analysis of the EEQSFOC technique with compared methods

Fig. 8 shows a detailed throughput analysis of the EEQSFOC model with other existing techniques under distinct IoT nodes. From the figure, it is obvious that the EEQSFOC method has resulted in ineffective performance by accomplishing a superior throughput. For instance, on the existence of 100 IoT nodes, the EEQSFOC model has showcased a maximum throughput of 0.98Mbps whereas the FEEC-IIR, AFSAC, FUCHAR, and NFRCF-RP algorithms have attained a minimum throughput of 0.94Mbps, 0.93Mbps, 0.92Mbps, and 0.90Mbps. Furthermore, on the existence of 300 IoT nodes, the EEQSFOC technique has depicted a superior throughput of 0.90Mbps whereas the FEEC-IIR, AFSAC, FUCHAR, and NFRCF-RP techniques have reached a reduced throughput of 0.72Mbps, 0.70Mbps, 0.68Mbps, and 0.65Mbps. Meanwhile, on the existence of 500 IoT nodes, the EEQSFOC approach has demonstrated an improved throughput of 0.82Mbps whereas the FEEC-IIR, AFSAC, FUCHAR, and NFRCF-RP techniques have attained a reduced throughput of 0.60Mbps, 0.58Mbps, 0.54Mbps, and 0.52Mbps.

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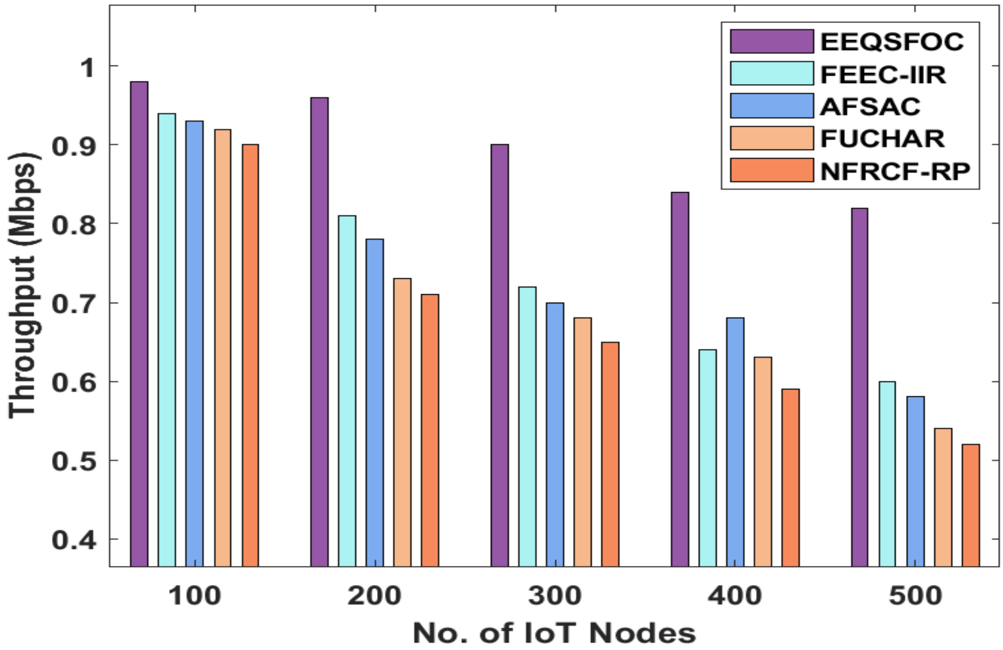

Fig. 8. Throughput analysis of the EEQSFOC technique with compared methods

Fig. 9 illustrates the results analysis of the EEQSFOC algorithm with other models interms of PLR. The figure exhibited that the EEQSFOC method has portrayed effective results under all varying IoT nodes. For instance, under the existence of 100 IoT nodes, the EEQSFOC technique has reached a lower PLR of 2% whereas the FEEC-IIR, AFSAC, FUCHAR, and NFRCF-RP methodologies have reached an improved PLR of 4%, 5%, 6%, and 7% correspondingly. In the meantime, under the existence of 300 IoT nodes, the EEQSFOC model has attained minimal PLR of 3% whereas the FEEC-IIR, AFSAC, FUCHAR, and NFRCF-RP techniques have attained a superior PLR of 6%, 7%, 8%, and 8% respectively. Afterward, under the existence of 500 IoT nodes, the EEQSFOC approach has obtained lesser PLR of 4% whereas the FEEC-IIR, AFSAC, FUCHAR, and NFRCF-RP algorithms have reached a higher PLR of 6%, 8%, 9%, and 10% correspondingly.

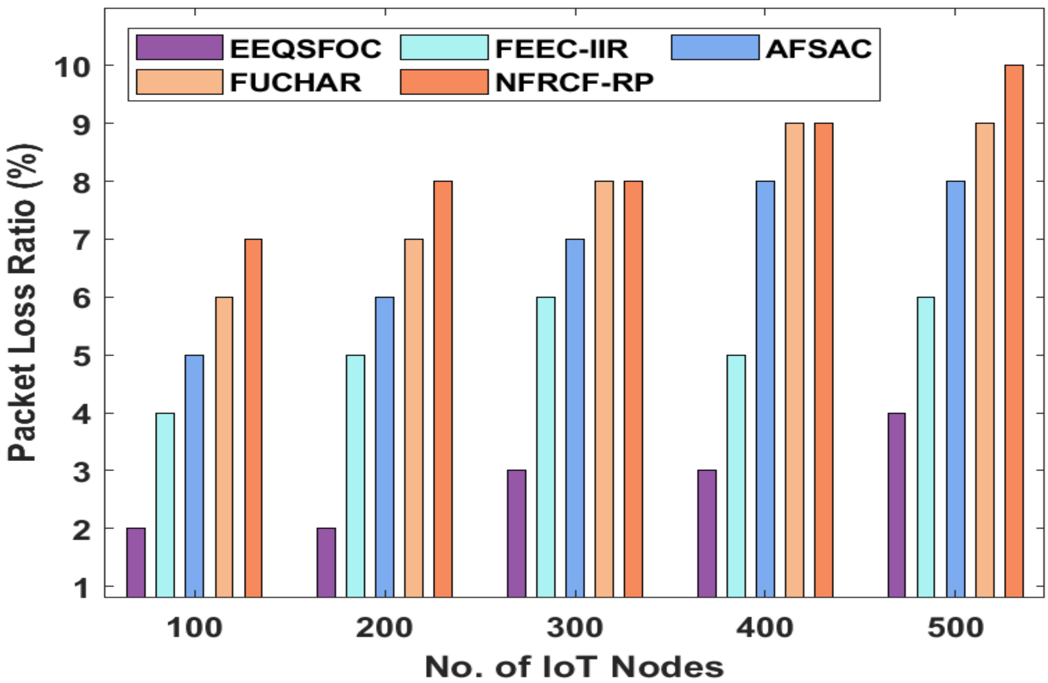

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Fig. 9. PLR analysis of the EEQSFOC technique with compared methods

5. Conclusion

This paper has developed a novel energy efficient clustering technique using EEQSFOC algorithm for IoT environment. Primarily, the IoT devices are arranged arbitrarily in the target region. Next, the IoT devices gather details about the neighboring IoT devices. Afterward, the EEQSFOC algorithm gets accomplished to elect an optimum set of CHs. In addition, quantum computing concept is combined with the SFO algorithm to expand the searching process, and attain better tradeoff among the exploration and exploitation capabilities. Subsequently, the elected CHs broadcast advertisements to construct clustering by linking nearby IoT devices as CMs. For confirming the capable energy efficient outcome of the EEQSFOC technique, a series of experimentations take place and the results are inspected interms of distinct measures. The experimental outcome ensured the betterment of the EEQSFOC technique over the existing clustering techniques.

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