



Energy Efficient Type II Fuzzy logic based Clustering with Quasi Oppositional Firefly based Routing Protocol for WSN-Assisted IoT System

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ABSTRACT

In recent times, the concept of Internet of Things (IoT) and Wireless Sensor Network (WSN) are integrated together to improve the sensor based communication in the near future applications. Since the IoT devices in WSN are battery powered, energy efficiency is regarded as a major design issue which needs to be solved. Clustering and Routing are considered as the important ways to achieve energy efficiency and network lifetime. In this view, this paper introduces a new energy efficient Type II fuzzy logic based clustering and quasi oppositional based learning firefly algorithm for routing in WSN assisted IoT networks, called T2FL-QOBLFF algorithm. The proposed T2FL-QOBLFF algorithm initially undergoes T2FL based clustering to select the optimal number of cluster heads (CHs) using residual energy (RE), distance to base station (DBS) and node degree (ND). Then, the QOBLFF based routing technique determines the optimal routes for inter-cluster communication process. The incorporated of quasi oppositional based learning (QOBL) in the firefly algorithm helps to increase the convergence rate and attains optimal set of solutions. A series of experiments were carried out to verify the goodness of the T2FL-QOBLFF model interms of energy consumption, network lifetime, packet delivery ratio (PDR), packet loss rate, throughput, and end to end delay.

Key words: IoT, WSN, Energy efficiency, Clustering, Routing

1. INTRODUCTION

IoT is an advanced method which concentrates in connecting massive number of sensor based devices. It plays a vital role in defining the problems and challenges involved while implementing IoT relied systems in today's world. Recently, the usage of sensor nodes has been improved with a capability to collect data with no manual power. The WSN [1] is

considered as the key activators for IoT concept because of the inception. It acts as an environment to develop diverse types of smart city domains like transportation and roadside fields, observing air pollution, modern parking system, automatic management, and alternate IoT centric models. WSN is one of the commonly applied methods inside an IoT that enables a numerous collection of sensor nodes for collecting data and route the packets effectively towards Base station (BS) or sink.

The IoT sensor nodes are linked to deploy WSN guided IoT network and compute data sensing in target region to transmit the sensed data to the destination. The data sensing as well as routing operations need reasonable data interchange between the nodes which results in maximum power dissipation. However, prominent energy application methods are essential for executing the Green IoT model. WSN are self-implied and composed of permanent multi-functional sensors with minimum battery which is distributed randomly over a remote site [2]. Figure 1 shows the functions of IoT model.

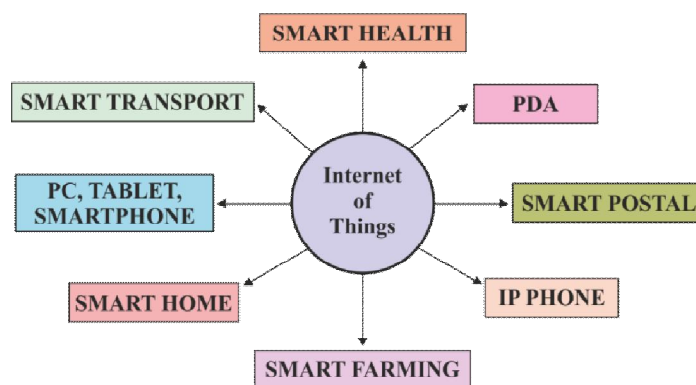


Figure 1: Applications of IoT

A fuzzy relied hierarchical clustering technique so called as LEACH-ERE [3] which utilizes power evaluation model to expand the network lifetime under the division of overhead. Addition to RE, the calculated RE has been used as a fuzzy

indicator at the time of CH election. [4] provided an approach to minimize the distance of multi-cluster as well as power utilization.

[5], concentrated to manage the power of a network which tends to enhance the duration of WSN by applying various attributes, such as battery model, fading model, and additional factors. It affects the data traffic produced in intra-cluster and inter-cluster communication. The researchers have applied the Alternating Direction Method of Multiplier (ADMM) for the purpose of computing best cluster radius. Furthermore, an adjustable smart CH election has been developed according to RE and maximum power application. [6] implied a dynamic clustering method to accomplish power efficiency in green IoT network. In order to compute clustering, these methods have applied the nodes' energy necessities and clusters' data association. Even though, the amount of data is not assumed in clustering function. According to path difficulty, pairs of nodes are developed and logical values are allocated and enable the load balance in all clusters. Also, it attempts to minimize clustering complexity by eliminating the nodes' position details. Hence, the prohibition of distance information results in irrelevant outcomes.

[7] projected an energy-based clustering protocol for heterogeneous networks with arbitrary node deployment. It also applies a hybrid model with LEACH and SEP, and divides the whole system as 2 sites. Initially, first region is composed of general nodes and latest nodes. Secondly, it is embedded with massive latest nodes. Hence, nodes in these 2 regions forward the data to sink with the help of hybrid clustering approach. [8] defined an efficient model for the limitation of power in green WSN by diverse energy supplies. It has divided the power cost reduction problem into 4 sub-problems and applied 4 various model to resolve such issues.

IHSCR [9] is an energy-efficient clustering protocol which supports an improved C-LEACH. It combines the C-LEACH discreet encoding method and wheel selection approach. The multilevel hybrid cluster relied routing protocol algorithm (MLHP) employs the strategy of predictive selection of CHs. Also, PSO-ECHS is defined as energy-efficient method guided by particle swarm optimization (PSO) for CH election in WSNs. It assumes the multi-cluster distance, BS distance and RE of sensor nodes. It mainly concentrates in accomplishing prolonged and effective WSN lifetime. In addition, [10] applied a multi-hop routing with grid clustering. It limits the power application sensor nodes by the combination of variables like energy, relative distance and regional density of the system. The CH overhead is minimized by proper distribution of work load.

Since clustering and routing are considered as the energy efficient techniques, this paper develops an energy efficient Type II fuzzy logic based clustering and quasi oppositional based learning firefly algorithm for routing in WSN assisted

IoT networks, called T2FL-QOBLFF algorithm. The proposed T2FL-QOBLFF algorithm involves two major processes namely T2FL based clustering and QOBLFF based routing. Initially, it undergoes T2FL based clustering to select the optimal number of CHs using residual energy (RE), distance to base station (DBS) and node degree (ND). Then, the QOBLFF based routing technique determines the optimal routes for intercluster communication process. The incorporation of quasi oppositional based learning (QOBL) in the firefly (FF) algorithm helps to increase the convergence rate and attains optimal set of solutions. A series of experiments were carried out to verify the goodness of the T2FL-QOBLFF model and the results are examined under several aspects.

2. THE PROPOSED T2FL-QOBLFFMODEL

The proposed T2FL-QOBLFF algorithm operates as follows. Figure 2 shows the work flow of the T2FL-QOBLFF algorithm. Initially, the IoT nodes are deployed in the target area and undergo initialization process for information discovery. Then, the T2FL based clustering process gets executed to select the optimal CHs using three parameters namely RE, DBS and ND. Followed by, the QOBLFF based routing process is applied for the selection of optimal routes from the IoT nodes to BS. WSN is composed of a number of sensor nodes and BS.

2.1 Type II Fuzzy Logic based Clustering Technique

The projected T2FLUCA is embedded with 2 phases: CH selection phase and cluster development phase. Initially, BS implements the presented model to select proper CHs for uniform load distribution. Secondly, the selected CHs can develop clusters with closer nodes. For CH and cluster size election, fuzzy logic (FL) [11] with 3 input parameters likes RE, DBS and ND have been applied.

Residual energy

The power is highly significant resource that is assumed in WSN. The CH is nodes intakes maximum energy when compared to CM if it computes the tasks like aggregation, processing and routing data. The RE is processed using given function.

$$E_r = E_0 - E_c \quad (1)$$

where the E_0 and E_c defines the initial energy and power applied by the node, correspondingly; and E_r implies RE of a regular node.

Communication cost

The forwarded message applies energy that is directly proportional to square of the distance over the candidate nodes and source node. The communication cost is described in the following:

$$C = \frac{d_{avg}^2}{d_0^2} \quad (2)$$

Where d_{avg} shows the maximum distance among the node and neighbors and d_0 showcases broadcasting range of a node.

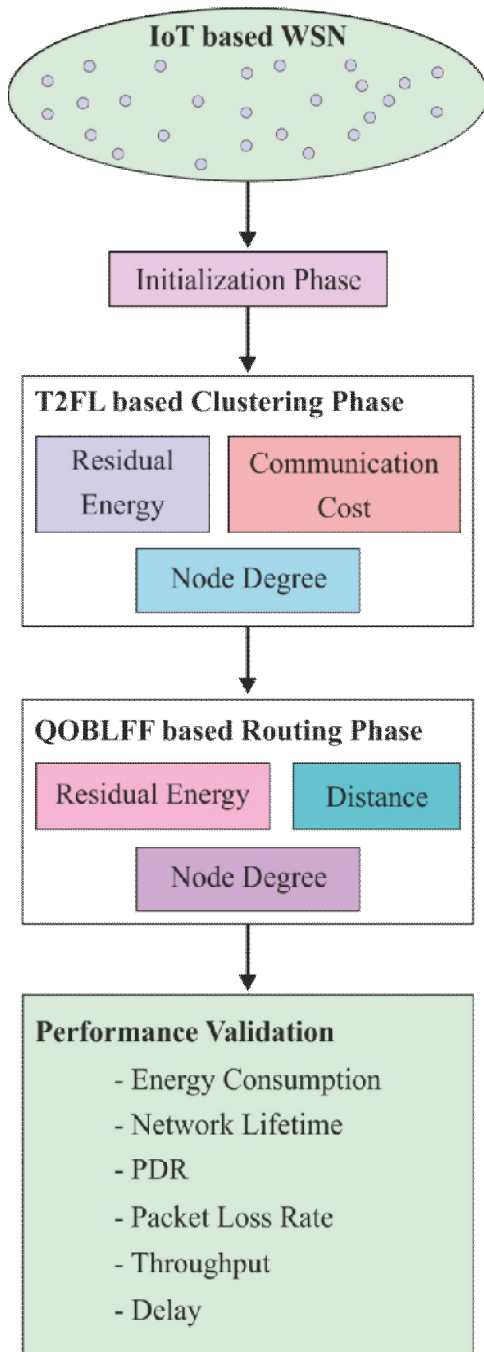


Figure 2: Block diagram of proposed model

Node Degree

The rule is that, the nearby neighbors model the better value; the greater probability a node is treated as CH. The count of neighbors is determined in the following:

$$D = \frac{|D_i - D_0|}{D_0} \tag{3}$$

Where, D_i implies the number of neighbors of a node and D_0 defines the best number of neighbors.

2.2 Quasi Oppositional based learning with Firefly (QOBLFF) Routing Algorithm

In this section, the QOBLFF based routing algorithm is applied for the identification of optimal routes between CHs and BS.

2.2.1 Firefly Algorithm

The FF technique depends on the brightness of the flashes. In this, 2 features restrict the illustration distance of FFs. In night, FFs is simply communicated over hundred meters. The flashes are capable to be created in a method that it is combined among the objective function to be enhanced which create it feasible for formulating novel optimization technique. The FF technique following principles:

- FFs are unisex
- Attractiveness depends upon the brightness of the flashlights; the smaller bright FF is concerned to the brighter FF.

The FF attractiveness is a monotonically a reducing function of distance $r_{uv} = d(x_v, x_u)$ for selecting FF, e.g. the exponential function.

$$r_{uv} = \|x_u - x_v\| \tag{4}$$

$$\beta = \beta_0 e^{-\gamma r_{uv}} \tag{5}$$

where β_0 is the attractiveness at $r_{uv} = 0$ and γ is the light absorption coefficient at the source. The progress of a FF u is disturbed to other FF v and is computed as

$$x_{u,k} \leftarrow (1 - \beta)x_{u,k} + \beta x_{v,k} + i_{u,k} \tag{6}$$

$$i_{u,k} = \alpha \left(rand 1 - \frac{1}{2} \right) \tag{7}$$

The particular FF x_u with highest fitness is goes in an arbitrary approach depend on the follows formulation.

$$x_{u,k} \leftarrow (1 - \beta) \tag{8}$$

$$x_{u^{max},k} \leftarrow x_{u^{max},k}^+ i_{u^{max},k} \tag{9}$$

$$i_{u^{max},k} = \alpha \left(rand 2 - \frac{1}{2} \right) \tag{10}$$

whererand $1 \approx U(0,1)$ rand $2 \approx (0,1)$ are random numbers obtained from regular distribution. The brightness of a FF is manipulated by the landscape of the objective function. The Cartesian distance among 2 FFs u and v x_u and x_v is calculated as,

$$r_{uv} = \|x_u - x_v\| = \sqrt{\sum_{k=1}^d (x_{u,k} - x_{v,k})^2} \frac{1}{\Gamma^m} \tag{11}$$

Where $x_{u,k}$ is the k^{th} module of the spatial coordinate x_u of the u^{th} FF. The r_{uv} in 2D space is computed in Eq. (12).

$$r_{uv} = \sqrt{(x_u - x_v)^2 + (y_u - y_v)^2} \quad (12)$$

The progress of a FF u is attracted to a brighter FF and is formulated as

$$x_u = x_u + \beta_0 e^{-\gamma r_{uv}^2} (x_v - x_u) + \alpha \epsilon_u \quad (13)$$

where 2^{nd} term signifies attraction and 3^{rd} term denotes the randomization. Now, α is the randomized parameter and ϵ_u is a vector of arbitrary numbers derivative from Gaussian or regular dispersion. Because of all FF works in an independent method, it is appropriate to corresponding execution. Figure 3 shows the Flowchart of FF method.

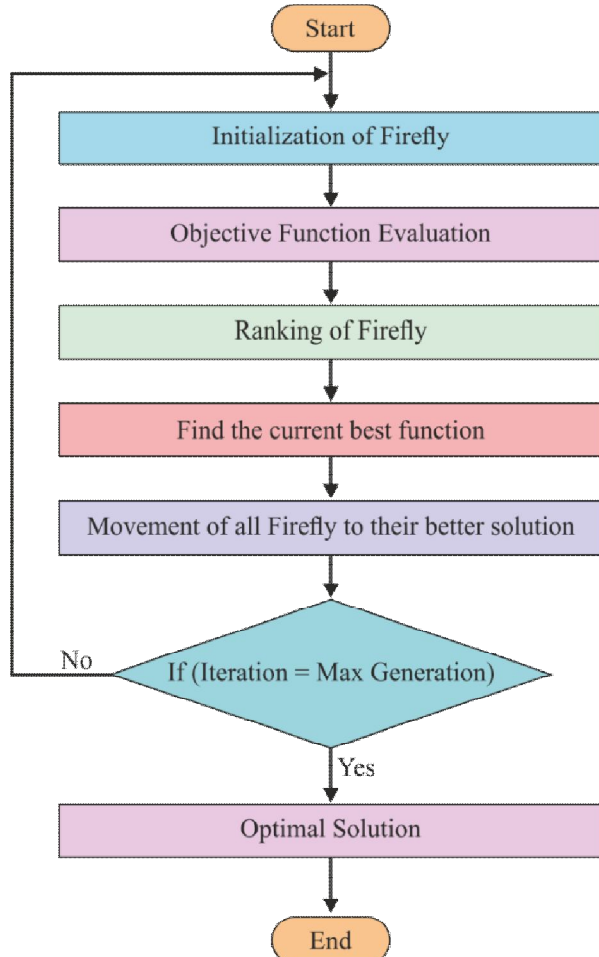


Figure 3: Flowchart of Firefly Algorithm

2.2.2 QOBL based Routing Process

In FF technique, a potential solution is signified by FF and count of FFs which are equivalent to the number of solution (N_f). The FFs $F_u, \forall u, 1 \leq u \leq N_f$ are composed of a position $X_{u,d}, \forall d, 1 \leq d \leq D$ and the dimension of FFs is represented by D . To enhance the solution, FF with minimum brightness move towards maximum brighter FF as depicted in Eq. (14). It is followed periodically until reaching the desired outcomes.

$$x_u = x_u + \beta_0 e^{-\gamma r_{uv}^2} (x_v - x_u) + \alpha \left(rand - \frac{1}{2} \right) \quad (14)$$

Where $\alpha \in (0,1)$ and β both are randomized parameter, $rand$ implies a random value, x_u illustrates the position of u^{th} FF and x_v denotes the position of v^{th} FF. It is utilized to determine the route from CH to the BS. It is achieved by using effective FF model which has to be embedded with RE, Euclidean distance as well as ND.

Algorithm for Routing

Steps to determine out closer better route [h]
 1. Initialize the FF Population using QOBL $F_u, \forall u, 1 \leq u \leq N_f$
 2. Compute the Intensity of all FFs
 While $u = N_f$
 $I_u = Fitness(F_u) / \text{use (7)}/$
 end
 3. $T! = \text{Max. iteration do}$
 Process of FF depends on light intensity
 while $u! = N_f$
 while $v! = N_f$
 if $(I_v > I_u)$ then
 for $k \leftarrow 1$ to m
 Move firefly $I_{u,k}$ to $I_{v,k} / \text{use (3)}/$
 Calculate the novel solution and updated light intensity.
 end for
 end
 end
 end
 Rank the present FFs and define the present optimal
 4. Compute $Next - Hop(CH_u), \forall u, 1 \leq u \leq m + 1$, (i.e., route ζ) utilizing $\max(fitness(F_u))$.

3. EXPERIMENTAL VALIDATION

Extensive set of experimental analysis were carried out to investigate the performance of the presented model. The parameter setting is provided in Table 1. Table 2 shows the comparative analysis of T2FL-QOBLFF model in terms of Various QoS Parameters.

Table 1: Simulation parameters

Parameter	Value
Area	1000×1000m
BS location	1000-1150m
Number of nodes	100
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: Result Analysis of Existing with Proposed Method in terms of Various QoS Parameters

No. of IoTNodes	Energy Consumption (mJ)					
	T2FL-QOBLFF	FF	FEEC-IIR	MOBFO-EER	FRLDG	TCBDGA
100	39	42	45	55	65	135
200	63	67	70	80	105	159
300	84	91	97	107	140	180
400	98	106	110	140	158	210
500	125	134	145	165	183	250
No. of IoTNodes	Network Lifetime (Rounds)					
	T2FL-QOBLFF	FF	FEEC-IIR	MOBFO-EER	FRLDG	TCBDGA
100	5800	5600	5500	5000	4800	4300
200	5600	5400	5200	4800	4600	4000
300	5300	5200	5000	4700	4400	3800
400	5200	5100	4900	4300	4100	3400
500	5000	4900	4700	4100	3900	3100
No. of IoTNodes	Packet Delivery Ratio (%)					
	T2FL-QOBLFF	FF	FEEC-IIR	MOBFO-EER	FRLDG	TCBDGA
100	99	99	99	98	97	95
200	99	99	98	97	96	94
300	98	97	97	96	94	92
400	98	97	96	95	93	90
500	A. 97	96	95	94	92	88
No. of IoTNodes	End to End Delay (sec)					
	T2FL-QOBLFF	FF	FEEC-IIR	MOBFO-EER	FRLDG	TCBDGA
100	2.10	2.15	2.20	2.80	4.10	5.70
200	2.60	2.90	3.70	4.90	5.20	6.50
300	3.30	3.60	4.80	6.10	6.40	7.30
400	4.20	4.80	5.60	7.80	8.10	8.40
500	5.80	6.00	6.20	8.90	9.30	9.40
No. of IoTNodes	Throughput (Mbps)					
	T2FL-QOBLFF	FF	FEEC-IIR	MOBFO-EER	FRLDG	TCBDGA
100	0.97	0.96	0.95	0.91	0.80	0.76
200	0.91	0.85	0.82	0.78	0.69	0.70
300	0.84	0.76	0.72	0.69	0.60	0.62
400	0.76	0.70	0.65	0.58	0.53	0.52
500	0.72	0.65	0.61	0.53	0.46	0.47
No. of IoTNodes	Packet Loss Ratio (%)					
	T2FL-QOBLFF	FF	FEEC-IIR	MOBFO-EER	FRLDG	TCBDGA
100	1	1	1	2	3	7
200	1	2	2	3	4	9
300	2	2	3	4	6	10
400	2	3	4	5	7	11
500	3	4	5	6	8	12

3.1 Energy Efficiency Analysis

Figure 4 shows the energy consumption analysis of the T2FL-QOBLFF algorithm under varying number of IoT nodes. The figure displayed that the TCBDGA algorithm has consumed maximum amount of energy under all the IoT nodes. At the same time, the FRLDG and MOBFO-EER models have exhibited somewhat better energy consumption outcome to a certain extent. Besides, the FEEC-IIR model has showed moderate energy consumption and surpassed all the compared methods except FF and T2FL-QOBLFF algorithms. Though the FF algorithm has demonstrated near optimal results with the low energy consumption, the T2FL-QOBLFF algorithm has showcased superior results by attaining lower energy consumption over the compared methods. For instance, under the node count of 100, the proposed T2FL-QOBLFF algorithm needs a minimal amount of energy of 39mJ whereas the FF, FEEC-IIR, MOBFO-EER, FRLDG and TCBDGA algorithms requires a higher amount of 42mJ, 45mJ, 55mJ, 65mJ and 135mJ respectively. Besides, under the least node value of 200, the projected T2FL-QOBLFF method requires a lower amount of power of 63mJ while the FF, FEEC-IIR, MOBFO-EER, FRLDG and TCBDGA methodologies needs maximum amount of 67mJ, 70mJ, 80mJ, 105mJ and 159mJ respectively.

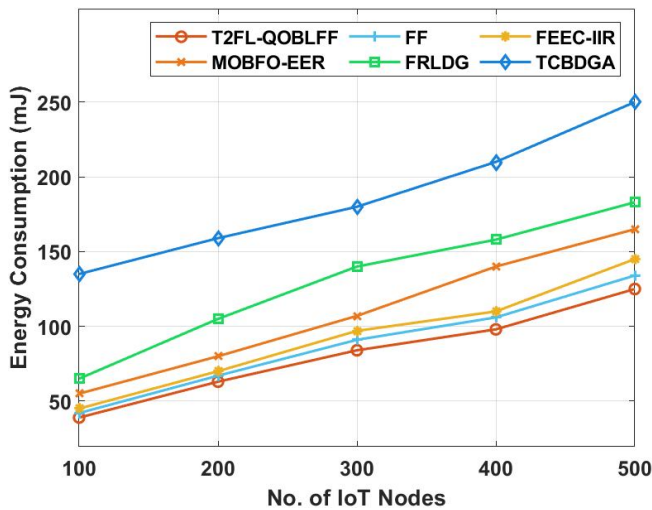


Figure 4: Energy consumptions analysis of T2FL-QOBLFF model in terms of Various QoS Parameters

3.2 Throughput Analysis

Figure5 depicts the throughput analysis of the T2FL-QOBLFF model under various number of IoT nodes. The figure portrayed that, the TCBDGA approach has implied least lifetime under all IoT nodes. Likewise, the FRLDG and MOBFO-EER approaches have showcased better throughput outcome to a certain extent. On the other side, the FEEC-IIR approach has exhibited reasonable throughput and surpassed all other previous models excluding FF and T2FL-QOBLFF methods. Though the FF approach has illustrates closer optimal results with the maximum throughput, the T2FL-QOBLFF algorithm has represented best results by reaching maximum throughput over previous approaches. For instance, under the node count of 100, the depicted

T2FL-QOBLFF algorithm provides a higher throughput of 0.97Mbps and the FF, FEEC-IIR, MOBFO-EER, FRLDG and TCBDGA models showcases a lower throughput of 0.96, 0.95, 0.91, 0.80 and 0.76 Mbps correspondingly. In the same way, under the node count of 200, the applied T2FL-QOBLFF approach provides a higher throughput of 0.91 Mbps while the FF, FEEC-IIR, MOBFO-EER, FRLDG and TCBDGA algorithms showcases a least throughput of 0.85, 0.82, 0.78, 0.69 and 0.70 Mbps correspondingly.

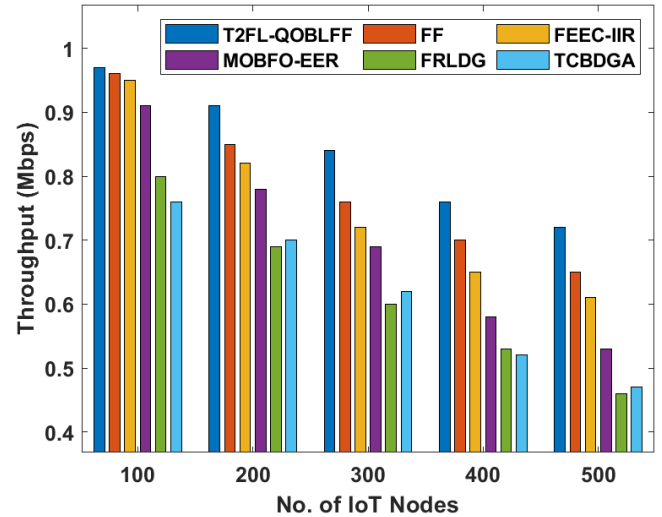


Figure5: Throughput analysis of T2FL-QOBLFF model in terms of Various QoS Parameters

4. CONCLUSION

This paper has developed an energy efficient T2FL-QOBLFF algorithm for IoT assisted WSN. The proposed T2FL-QOBLFF algorithm involves two major processes namely T2FL based clustering and QOBLFF based routing. Initially, the IoT nodes are deployed in the target area and undergo initialization process for information discovery. Then, the T2FL based clustering process gets executed to select the optimal CHs using three parameters namely RE, DBS and ND. Followed by, the QOBLFF based routing process is applied for the selection of optimal routes from the IoT nodes to BS. An extensive set of experimentation is carried out to assess the effective performance of the T2FL-QOBLFF algorithm. The experimental outcome stated that the T2FL-QOBLFF algorithm is found to be superior to compared methods in terms of energy consumption, network lifetime, PDR, packet loss rate, throughput, and end to end delay.

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