TFUZZY-OF: a new method for routing protocol for low-power and lossy networks load balancing using multi-criteria decision-making

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ABSTRACT

The internet of things (IoT) based on a network layer perspective includes low-power and lossy networks (LLN) that are limited in terms of power consumption, memory, and energy usage. The routing protocol used in these networks is called routing over low-power and lossy networks (RPL). Therefore, the IoT networks include smart objects that need multiple routing for their interconnections which makes traffic load balancing techniques indispensable to RPL routing protocol. In this paper, we propose a method based on fuzzy logic and the technique for the order of prioritization by similarity to the ideal solution (TOPSIS) as a well-known multi-criteria decision-making method to solve the load balancing problem by routing metrics composition. For this purpose, a combination of both link and node routing metrics namely hop count, expected transmission count, and received signal strength indicator is used. The results of simulations show that this method can increase the quality of services in terms of packet delivery ratio and average end-to-end delay.

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1. INTRODUCTION

The internet of things (IoT) as a new idea in the world of networks was introduced in [1]. IoT is a system consisting of computing devices or objects including radio frequency identification (RFID), near-field communication (NFC), sensors, actuators, and mobile phones that possess the capabilities for transferring data over a network. The IoT and its services are used in a variety of areas such as agriculture, energy, home and building, smart cities, healthcare, industry, transportation, and many other areas. One of the most important features of IoT is the heterogeneity of objects. Given that many objects and physical and virtual identities around us are interconnected in IoT, a large amount of heterogeneous data must be computed in IoT networks [2]–[9].

One of the key components of IoT is the low-power and lossy networks (LLNs) [10], a set of interconnected tiny, lossy, and low-powered devices which are limited in terms of energy, memory, and computational power. To design a standard routing protocol for IoT, the internet engineering task force (IETF) introduced a new 6LoWPAN-compliant routing protocol for LLN networks called routing over low-power and lossy networks (RPL) [11]. The RPL routing protocol is a distance-vector protocol that organizes nodes as destination-oriented directed acyclic graphs (DODAG) based on a collection of routing metrics in a network.

Moreover, parent selection for each node in the network is done via objective functions (OF). As a default in RPL, there are two OFs namely objective function zero (OF0) [12] and minimum rank with hysteresis objective function (MRHOF) [13] for parent selection by a single routing metric that is unable to handle heavy network traffic. Therefore, traffic load balancing problems in RPL-based networks are very important.

In this paper, we concentrate on load balancing in the RPL-based networks using fuzzy logic [14] and multi-criteria decision-making (MCDM) [15] methods. The MCDM method can be used for load balancing in RPL-based networks as an appropriate technique and promising approach. The major contributions of our paper are that we i) represent a comprehensive study of load balancing in the RPL-based networks based on various routing metrics, ii) introduce a novel objective function by combining three routing metrics namely hop count (HC), received signal strength indicator (RSSI), and expected transmission count (ETX), iii) use fuzzy logic and the technique for the order of prioritization by similarity to ideal solution (TOPSIS) [16] method as a well-known MCDM technique for best parent selection in RPL, and iv) implement and evaluate the proposed method using Cooja [17] simulator based on Contiki-NG operating systems in terms of two performance metrics: packet delivery ratio (PDR), average end-to-end delay (E2ED).

The idea behind the usage of mixed link and node metrics arrives from the constraints that a single metric supplies. The best parent selection is one advantage of the objective function with a single metric, but it also has certain restrictions. It is obvious that a single metric technique increases some performances but may decrease others, leading to the conclusion that the single metric approach does not fully meet the needs of the application. For this purpose, we proposed a combination of both link and node metrics namely hop count, RSSI and ETX. The rest of this paper is structured as follows. The RPL protocol and objective function in RPL are introduced in section 2. Section 3 presents the related works. The proposed method is described in section 4 and evaluated in section 5 and finally, the conclusion is discussed in section 6.

2. PRELIMINARIES

2.1. The RPL routing protocol

The RPL is a distance-vector routing protocol according to the destination-oriented directed acyclic graphs (DODAG). There is some basic terminology, and key concepts in RPL must be described as follows [4], [10]. A directed acyclic graph (DAG) refers to a graph that has no cycle in the network. DODAG root (Sink) manages LLN nodes and gathers local data, and finally connects LLN nodes to the internet as an edge router. Destination-oriented DAG (DODAG) is a loop-free tree structure of nodes forming a network which have a single border router connecting the network to an IPv6 backbone, this network is identified by a DODAGID tag. The objective function (OF) is a set of rules and policies that a node uses to select the optimal path with respect to the application requirements such as minimum energy consumption or residual energy. RPL instance is a network comprised of one or more DODAGs that have identical OF and are identified by RPLInstanceID. Rank is the distance from the root (sink) node. For each node, the distance must be greater than the Rank of its parent node to avoid routing loops in the DODAG. The DODAG version is a tag manipulated by a border router in DODAG. Goal refers to where a DODAG demands to attain and may be a wired or wireless network. Grounded is when a DODAG attained its goal. Floating is when a DODAG does not reach its goal. A storing mode keeps a downward routing table at each node of DODAG, while a non-storing mode sends all traffic to the root node, and finally, it sends traffic to the children's nodes. DODAG parent means that a parent of a node (child) is another node on a path toward the root node. The parent has a lower rank than its children's nodes. DODAG sibling means that a sibling of a node in the DODAG is any neighbor node that is placed at the same rank. Sub-DODAG refers to every subtree belong a DODAG.

RPL routing protocol uses four types of control messages [18], [19], which are DODAG information object (DIO), DODAG information solicitation (DIS), DODAG advertisement object (DAO), destination advertisement object acknowledgment (DAO-Ack). To construct DODAG, the sink or root starts to propagate DIO messages through the network. The nodes receiving a DIO control message decide whether to connect the DODAG or not based on the OF. Joint nodes re-propagate the DIO message, and this process will take until all nodes join and construct a tree.

2.2. Objective function

As we mentioned in section 1, there are two different standard OFs namely OF0 and MRHOF. The OF0 considers the hop count as a routing metric to find the shortest path to the root. Considering only hop count as the only metric in OF0 may cause low link quality, short lifetime, or unreliable path in LLNs. To overcome the mentioned problem in OF0, the MRHOF is proposed to select the path with the lowest cost. It uses the ETX metric to calculate the cost of each path. The most popular routing metrics can be separated into node metrics and link metrics groups [20]. The composite routing metrics should be well-defined and scalable. Table 1 shows the classification of some routing metrics.

Table 1. Classification of routing metrics in the RPL

Metric Group	Metric Name	Description
Node Metrics	Hop count (HC)	The number of hops among nodes in terms of the node's distance from the root.
	Energy consumption (EC)	This metric shows the energy spent in the network via sensor nodes.
	Residual energy (RE)	This metric refers to the remaining energy present in the network.
	Buffer occupancy (BO)	The data packets before forwarding in the wireless channel are stored in the buffer of nodes. This metric refers to how much the buffer of the node is occupied.
Link Metrics	Expected transmission count (ETX)	The number of expected transmitted count for packets to successfully receive at the destination, called ETX.
	Expected transmission time (ETT)	This metric refers to the expected time at the MAC layer for successful packet forwarding.
	Expected Lifetime (ELT)	This metric is defined based on the energy consumption of nodes in listening and transmitting modes (i.e., Rx and Tx).
	Received signal strength indicator (RSSI)	The RSSI is a famous radio link estimator and is defined as the power measurement in received signals.

3. RELATED WORKS

Several research on load-balancing techniques and the enhancement of OFs performance in RPL have been published recently. OF0 [12] uses hop count (HC) as a routing metric to carry out parent selection. In other words, the shortest path is selected from each node to the root during DODAG construction. Using hop count as the only metric may consider parents with poor connectivity. Thus, MRHOF [13] was proposed to resolve this problem by using a hysteresis mechanism besides the selection of a low-rank path. On the other hand, most previous versions of RPL use OF0 or MRHOF as their default OF, whereas other researchers like Gaddour *et al*. [21] merge them with their proposed idea. Popular routing metrics such as hop count or ETX or merging them are very common in research papers. In another work, the lexical metric composition of two routing metrics is defined as follows: The first metric providing low or high value would be used to choose the best parent among candidates. If the value of the first metric is equal for two or more candidates, the second metric would be checked to choose the best parent. Additive metric composition is another common technique in which a set of metrics are merged to provide one common metric. Many researchers have used these two techniques, such as Nassar *et al.* [22], who presented an additive metric called OFQS. The OFQS is the result of a combination of ETX, power state, and delay. Simulation results showed that OFQS performed better than MRHOF and OF0 in terms of E2ED, network lifetime, and PDR. In [23], a new load-balancing algorithm named smart energy efficient objective function (SEEOF) was proposed. In SEEOF an additive metric constructed from drain rate with the residual energy is provided. The simulation results depict that the SEEOF improves PDR and network lifetime in comparison with MRHOF and OF0.

In [24], a modified trickle mechanism for RPL protocol is presented. Due to the balanced load and optimized trickle mechanism, the network lifetime has increased in this method. Santiago *et al.* [25] proposed a technique using the nested un-weighted pair group method with event rate (UPGM) to address the load balancing problem of RPL. This method could enhance network lifetime, while scalability and overhead did not examine. Taghizadeh *et al.* [26] concentrated on network lifetime and packet loss under dynamic and heavy loads. The authors of this paper introduced the context-aware and load-balancing RPL (CLRPL) load-balancing protocol, a context-aware load-balancing technique. First, the authors introduced a novel objective function called context-aware objective function (CAOF) that uses a combination of remaining energy, parent rank, and ETX routing metrics for the calculation of the node's rank. Second, for the sake of load balancing, the authors introduced a novel metric called context-aware routing metric (CARF) which considers the node's context and uses remaining energy and queue utilization. The results of simulation via Cooja show that the CLRPL compared with the standard RPL improves the network lifetime and reduces packet loss ratio and overhead

4. THE PROPOSED METHOD

In the RPL protocol, the objective function is responsible for topology construction via proper parent selection in a DODAG. The routing metrics may be utilized in the defined objective function to calculate the Rank of a node as a single or combined multiple metrics. Lexical, additive, and fuzzy logic are common ways to combine different metrics. MCDM methods have become quite popular in network-related fields in recent years. In this paper, we are going to use the MCDM and fuzzy logic methods. The MCDM is an advanced tool in order to address complex decision problems involving multiple criteria goals. Lexical and additive are simple ways to address decision-making problems compared to MCDM and fuzzy logic approaches. The main goal of using the fuzzy logic method and TOPSIS technique is to integrate node and link metrics namely ETX, RSSI, and hop count. In our proposed method, the membership function is used to enable a rigorous assessment of the quality of the selected neighbor nodes. In order to meet various LLN requirements, including those for real-time and dependable applications, the TFUZZY-OF was designed.

4.1. Fuzzy logic

We were able to convert many input variables into a single output using the fuzzy logic approach [27]. The fuzzy process model [28] is divided into four parts, as shown in Figure 1. We utilize the Mamdani model [29] as the most prevalent fuzzy inference approach in this study, as follows. Fuzzification captures predetermined input variables and computes membership degrees for appropriate fuzzy set values. Fuzzy inference is the process of mixing fuzzified inputs and computing a fuzzy result. If the output is dependent on more than one rule, aggregation unites all values into one. Defuzzification, based on the preceding step, turns the fuzzy output to a precise value.

We define three metrics namely hop count, RSSI, and ETX for fuzzy logic composition. Figure 1 shows the fuzzy process model in which ETX and RSSI routing metrics as link metrics and hop count as node metrics are taken into account, respectively. In fuzzy logic, variables can be in ranges of true or false which are determined by linguistic values. To prepare one output, fuzzy logic uses linguistic variables to indicate the degree of reliance across metrics. The fuzzy set values are introduced based on the input variables' behavior [27]. The fuzzy values are entered into the fuzzy algorithm to decide on parent change.

In this method, the membership functions set for ETX, hop count, and RSSI are shown in Figures 2 to 4, respectively. A favorable path has to have high RSSI, low ETX, and low hop count. Figure 2 illustrates the membership function graph for the reverse normalized ETX in the proposed method. Based on this figure, a higher reverse normalized parameter value signifies a lower ETX for the route. As shown in the figure, the range of membership function is considered as low, medium, and high. Figure 3 shows the membership function graph for the reverse normalized hop count in the proposed method. If the reverse normalized hop count is high, it is desirable. As shown in the figure, the range of the reverse of the normalized hop count in membership functions is considered as low, medium, and high. Figure 4 displays the membership function graph for RSSI. It is obvious that the route will be preferred if the normalization value is high. As shown in the figure, the range of RSSI in membership functions is considered as low, medium, and high.

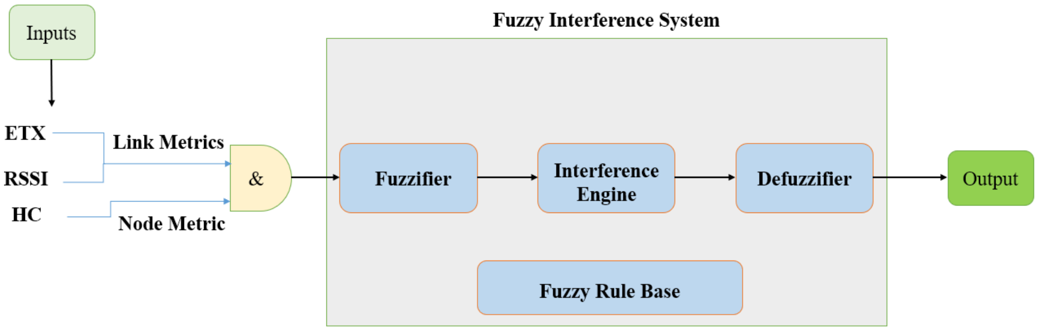


Figure 1. The fuzzy process model for the proposed method

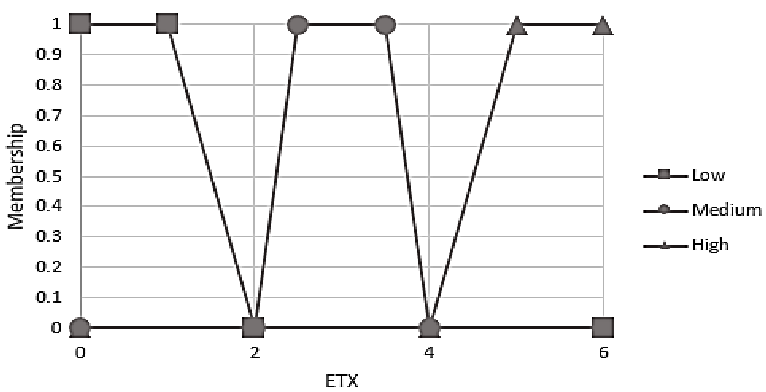


Figure 2. The graph of ETX membership function

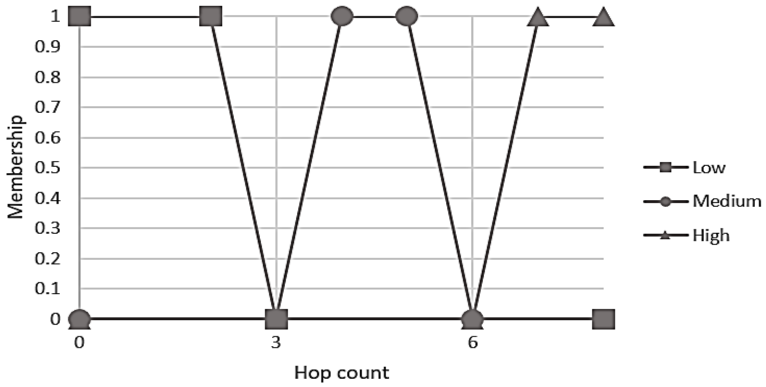


Figure 3. The graph of hop count membership function

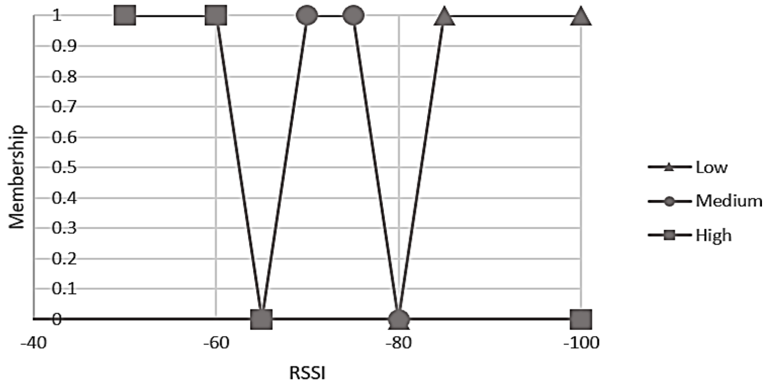


Figure 4. The graph of RSSI membership function

4.2. TOPSIS method

RPL uses the objective function to construct a path to the destination in order to effectively make the connection, which is one of its key features. The designers can provide various metrics in accordance with their requirements due to the inclusion of the objective function in the core of RPL. In this paper, we used the TOPSIS method as a well-known MCDM approach that was proposed by Hwang and Yoon [16] for the first time. For this purpose, we focus on the TOPSIS method to combine three routing metrics (i.e., hop count, RSSI, and ETX) and design a novel objective function for the selection of the parents called TFUZZY-OF. The TFUZZY-OF for solving the load balancing problem chooses the best parent node from a set of available parents' sets that is considered as a less or non-congested parent in the network using multiple routing metrics. Here, the best word refers to the best option for a node to be a parent in the network for optimal route and better performance through specific routing metrics. The parents and routing metrics in RPL are alternatives and criteria in the TOPSIS method, respectively. The TOPSIS method has 7 steps to produce the comparison between the candidate parents [16].

a) The TOPSIS method gets the decision matrix as an input in which each node acts as a decision-maker. This matrix contains m alternatives (candidate parents) A={a_i, $i = 1, 2, \ldots, m$} and n criteria (routing metrics). In this paper, we used 3 routing metrics C={C_j, j = 1, 2, 3} namely hop count, ETX, and RSSI to find the best parent. The x_{ij} displays the numerical value of the *j*th criteria for the *i*th choice. To determine the profits or costs of each criteria, the value of each must first be determined. It is self-evident that qualitative criteria (measured on a scale) must be replaced by quantitative metrics. This approach also contains an additional input that sets the relative relevance of each criterion to the others. The decision-maker weights vector $W = \{w_j, j = 1, 2, 3\}$ where $\sum_{j=1}^{3} w_j = 1$ is what it is called. Therefore, we have a matrix *(*x_{ij}*)*mn as (1).

$$D = \begin{bmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{bmatrix} \tag{1}$$

Each alternative choice is treated as a point in space in the TOPSIS approach. Then, using the two crucial points known as the positive ideal answer (A^+) and the negative ideal answer (A^-), each point's Euclidean distance is determined. The next step is to rate the points based on their distance from the positive and negative ideal answers.

b) The decision matrix *(x_{ij})*mn is normalized using the vector approach. The vector normalizing is determined as (2).

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum x_{ij}^2}}, i = 1,2, \dots, m, j = 1,2, \dots, n \tag{2}$$

The normalized matrix *(rij)*mn using the normalization method is computed as (3):

$$R_{ij} = \begin{bmatrix} r_{11} & \cdots & r_{1n} \\ \vdots & \ddots & \vdots \\ r_{m1} & \cdots & r_{mn} \end{bmatrix} \tag{3}$$

This is accomplished to rule out the problem's size, as each criteria may have its own unit of measurement.

c) The weighted normalized decision matrix *V* is created by multiplying each criteria's weight by the column in the normalized matrix that corresponds to that criterion as (4),

$$v_{ij} = w_j r_{ij}, i = 1,2, \dots, m, j = 1,2, \dots, n \tag{4}$$

where w_j is the original weight given to the indicator *vj*. Assume that $W = (w_1, w_2, \dots, w_j, \dots, w_n)$ is the weight matrix for the desired criteria, multiplying the first column by w_1, and the second column by w_2, and therefore multiplying the n_{th} column by w_n, as (5):

$$V = \begin{bmatrix} v_{11} & \cdots & v_{1n} \\ \vdots & \ddots & \vdots \\ v_{m1} & \cdots & v_{mn} \end{bmatrix} \tag{5}$$

d) Determining positive ideal options or benefits (A+) and negative ideal options or costs (A-), as shown in (6) and (7),

$$A^+ = \{(max v_{ij} | j \in J), (min v_{ij} | j \in J') | i = 1, 2, 3, \dots, m\} = \{v_1^+,\ v_2^+, \dots,\ v_n^+\} \tag{6}$$

$$A^- = \{(min v_{ij} | j \in J), (max v_{ij} | j \in J') | i = 1, 2, 3, \dots, m\} = \{v_1^-,\ v_2^-, \dots,\ v_n^-\} \tag{7}$$

where *J* is the profit criterion and *J'* is the cost criterion.

e) Determine the geometric distance of each alternative to A^+ (benefits) and A^- (costs). The 2-dimensional Euclidean distance is used to determine how far apart each ideal choice is, both positive and negative. Assume S_i^+ is the *i*th distance choice for A^+ and S_i^- for A^- as illustrated in (8) and (9).

$$S_i^+ = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^+)^2}, i = 1,2, \dots, m \tag{8}$$

$$S_i^- = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^-)^2}, i = 1,2, \dots, m \tag{9}$$

f) For each option *i*, we calculate d_i as (10).

$$d_i = \frac{S_i^-}{S_i^- + S_i^+}, i = 1,2, \dots, n, 0 \le d_i \le 1 \tag{10}$$

As can be seen, the relative distance weights between the *i*th alternative and the negative ideal are represented by this index. As a result, if the quantity of di for each choice is greater, the negative ideal distance will be greater and the rate will be higher. A^{i} is positioned on A^+ with $d_i = 0$ in the best situation, and on A^- with $d_i = 1$ in the worst case. The objective function for the new DIO message is defined based on three routing metrics including hop count, ETX, and RSSI based on (10) and using positive and negative ideals and then, in step 7, rank is calculated according to the objective function.

g) Rank the alternatives based on d_i, $i = 1,2,\dots,n$. The quantities collected in step 6 are compared. When the amounts are higher, it indicates that the situation is better. In this paper, according to the nature of the TOPSIS method, all criteria values of each alternative must be available in the best choice selection procedure. This causes increasing routing overhead because each node needs to send each criteria value to its neighbors in the DIO message. So, we use a modified TOPSIS method, such that each node uses the fixed positive and negative ideal.

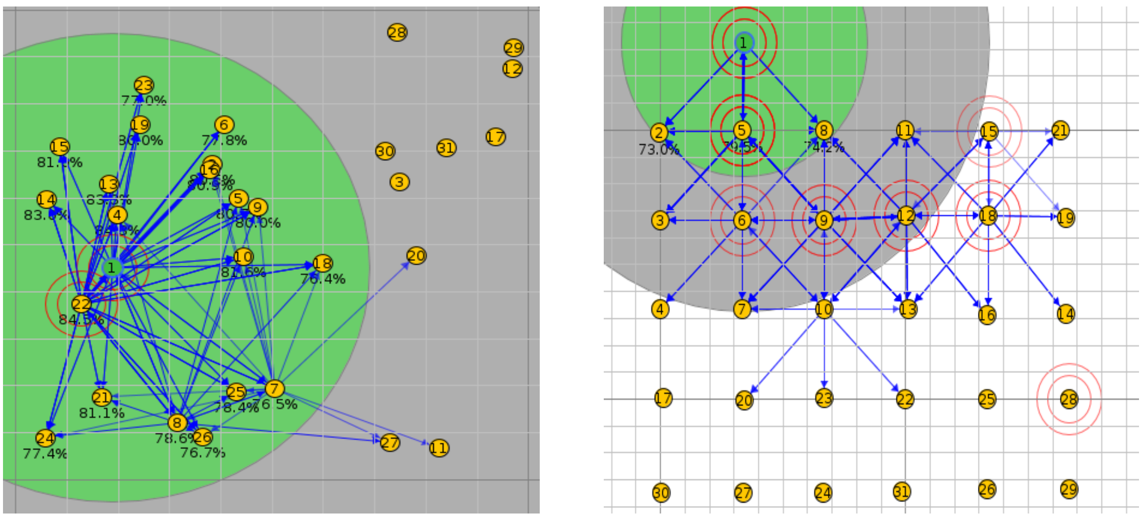
5. RESULTS AND DISCUSSION

To implement TFUZZY-OF, we used the Cooja [17] simulator running on Contiki-NG Operating System (version 3.0). It is an open-source emulator created for IoT purposes. In this paper, Z1 [30] mote is used as the base node for simulation. The network's nodes have a communication range of 50 meters and an interference range of 100 meters. Table 2 lists the parameters utilized in the simulations. For evaluation two metrics are taken into account: E2ED (the average time it takes for a packet to go from a client to a server node in a network is known as the average E2ED) and PDR, where the ratio of data packets successfully received at the destination to the amount transmitted during simulation is used to measure network dependability.

Table 2. The parameters considered in simulation

Network Parameters	Values
Sensor node OS	Contiki-NG
Simulator	Cooja
Routing protocol	RPL
Radio medium model	UDGM: distance loss
Deployment type	Random, Grid
Range of nodes	Rx and Tx: 50 m, Interference: 100 m
Mote type	Z1
Deployment area size	100×100 m
Number of client nodes	10, 20, 30
Number of server	1
TX ratio	60%
RX ratio	60%
Simulation duration	10 min

To evaluate the performance of TFUZZY-OF, RPL networks with 10, 20, and 30 nodes (1 node as server node and other nodes as client nodes) are considered that are located in two main topologies: random and grid. Figure 5 depicts the two primary topologies in which the LLN nodes are distributed across the experiment including random topology in Figure 5(a) and grid topology in Figure 5(b). As shown in the figures, the green color indicates the server node and the yellow color represents the client nodes.



(a) (b)

Figure 5. Nodes distribution with 1 (ID:1) server based on two topologies (a) random topology and (b) grid

The standardized OF-MRHOF, OF-fuzzy, and our novel TFUZZY-OF have all been compared. All simulation figures demonstrate RPL performances by analyzing the PDR and E2ED. In Figure 6, TFUZZY-OF has been compared to currently used OFs known as OF0 and MRHOF and also recently proposed OFs OF-EC and OF-fuzzy. As its observable in this figure, TFUZZY-OF has a good PDR rate almost close to 100% (98%). It can also be seen that this proposed method has outperformed every other OF by at least 10 percent increase in the amount of PDR. In Figure 7, TFUZZY-OF is compared to MRHOF and OF0 based on average E2ED. It is clear that the TFUZZY-OF has a lower average E2ED in comparison with both of them. From this figure, it is observable that for more populated LLN networks (in this experiment, networks with 20 and 30 nodes), TFUZZY-OF would outperform almost all the other objective functions since it seems that the E2ED decreases with a sharper steep as the number of nodes increases in a network.

With various network sizes, an OF with a single metric supplies high control messages than OF with combined metrics. As a result, the network should update, taking into account the available nodes, in the case of a link failure or a bottleneck node. However, in the network with combined metrics, link failures or bottleneck nodes are reduced because of using link and node metrics in the parent selection procedure.

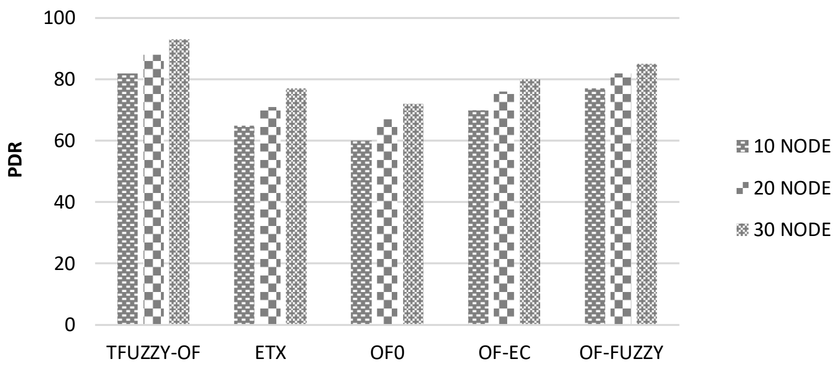


Figure 6. Comparison of PDR for three OFs

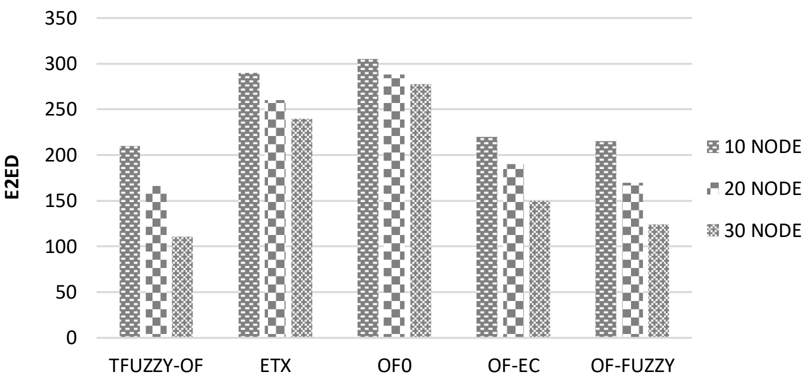


Figure 7. Comparison of E2ED for three OFs

6. CONCLUSION

The load balancing techniques play a crucial role in RPL routing protocol. In order to meet various LLN requirements, including those for real-time and dependable applications, the TFUZZY-OF as a new method was designed. In this paper, the TFUZZY-OF for load balancing of route establishments in RPL routing protocol has been proposed which uses the composition of a set of network metrics, here ETX, RSSI, and hop count, and a decision-making algorithm named TOPSIS. The proposed routing protocol is able to balance loads of traffic in a dense network and increase the lifetime of the network. To evaluate the proposed routing protocol, Cooja simulator is used, and the result is compared with standard RPL using MRHOF and also OF-EC and OF-fuzzy in terms of PDR and E2ED. Simulation results show that the TFUZZY-OF can increase the quality of service for LLN networks. For future work, the TFUZZY-OF will extend by using artificial intelligence techniques such as machine learning and deep learning methods, especially reinforcement learning to acquire more precision.

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