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Novel Geodetic Fuzzy Subgraph-Based Ranking for Congestion Control in RPL-IoT Network

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Abstract: Congestion control is among the most challenging tasks in enhancing QoS in the Internet of Things (IoT). Currently, wireless networks are able to have a large number of connections but with a limited amount of network resources. Consequently, congestion occurs, which adversely affects throughput, transmission delay, packet losses, power consumption management, and the lifespan of a network. This is certainly relevant in networks where transmissions are controlled by the Routing Protocol for Low-Power and Lossy Networks (RPL), which is commonly employed in the Internet of Things network. To solve this problem, a novel Geodetic fuzzy subgraph-based ranking (GFSR-RPL) for congestion control is proposed. Initially, the proposed GFSR-RPL selects the cluster head using K-means clustering. Then the rank calculation can be done via the final route setting for data transmission. A route setup scheme consists of three elements: 1) a Round Trip Time (RTT) estimator that assesses congestion conditions in a variety of ways; 2) a trend and relative strength indicator analysis; and 3) a geodetic fuzzy subgraph rank calculation method that calculates initial RTO (initial retransmission timeouts) accurately. The proposed GFSR-RPL method reduces the energy consumption of up to 43.58%, 25.8%, 14.82% and 6.85% than existing methods such as RPR, CBR-RPL, ACW and ECLRPL.

Keywords: clustering; geodetic fuzzy subgraph; internet of things; routing protocol for low-power and lossy networks; routing

1 INTRODUCTION

The Internet of Things (IoT) is a popular concept that connects a large number of smart and interactive devices, including sensors that will enable the world to be enhanced with both physical and virtual elements [1, 2]. A number of Internet-enabled devices, such as RFID tags [29] and wireless sensor nodes are linked to the Internet and can detect status and condition. They also have access to existing algorithms and potential trigger devices which has led to an extremely effective smart environments in construction, healthcare, etc [3, 26]. An IoT system typically comprises battery-operated, tiny gadgets that collect information from the outside world.

For sharing data, IoT devices rely on low-power connectivity protocols and limited computational capabilities. [4, 27]. IoT sensors often have battery life, reliability, memory, etc. resources. In order to address these difficulties, several solutions have been developed, including low-power wireless personal area networks (6LoWPANs). IEEE, ZigBee and IETF, have been developing protocols to help devices with limited resources communicate successfully in recent years [5, 28].

IPv6 Routing Protocol for Low Power and Lossy Networks (RPL) has been endorsed by the Internet Engineering Task Force (IETF) as the default routing protocol for IoT [6]. RPL is based on a graph-based platform referred to as Destination Oriented Directed Acyclic Graph (DODAG) that serves as the substructure for all routing protocol operations [7]. The DODAG graph is a semi-tree, and all of its edges are pointed in the direction of the root.

Although RPL is typically used with low-rate traffic, it needs to be able to handle high-volume traffic. Due to the possibility that nodes may create and forward large amounts of traffic towards the root, leading to congestion at parent nodes in a sensing region, this may result in congestion at parent nodes [8]. When there is congestion, client nodes cannot effectively set retransmission timeouts, resulting in unnecessary retransmissions. This overhead increases network congestion. An unbalanced traffic flow in a network leads to packet losses, delays, and power consumption control, all of which shorten the network's lifespan [9]. In order to solve this problem, an innovative geodetic fuzzy subgraph-based ranking method (GFSR-RPL), has been proposed. The major contributions of the framework are as follows:

- The major goal of the suggested GFSR-RPL system is to control the congestion in IoT network for the effective utilization of network resources.
- Initially, k-means clustering algorithm has been used to cluster the nodes in the network for reducing energy consumption.
- Second, when congestion is observed, an RTT estimator creates auxiliary parameters to alter the initial retransmission timeouts (RTO) and back off ratio.
- A relative strength indicator and trend analysis are used in the accurate initial RTO design to provide the precise first RTO estimation.
- Finally, geodetic fuzzy subgraph reduces retransmission overhead by adjusting the RTO using a flexible back off mechanism whose inputs are related to congestion.

The rest of the proposed work has been arranged as follows. The literature survey is explained in section 2. The proposed GFSR-RPL technique for congestion control is explained in section 3. The performance evaluation of the proposed method is provided in section 4. Conclusion and future enhancement are provided in section 5.

2 LITERATURE REVIEW

In LLNs, RPL is the most popular data routing method, which has undergone numerous improvements to alleviate routing congestion. Many techniques have been proposed to tackle the congestion problem in routing. Some of those techniques have been briefly examined in this section.

In 2019, Yao, H. et al. [16] proposed load-balancing routing on the basis of machine learning for congestion control in wireless networks that takes multiple factors into account, such as routing hops, delay, and topology. Compared with Bellman-Ford (BF) and its variant (QUBF) shortest path algorithms, their proposed machine learning-based routing technique performs better when measuring packet loss ratios, throughput, and delay.

In 2021, Farag, H. and Stefanovi [17] presented a Q-learning approach to reduce congestion in node and improve load balancing. Every node uses Q-learning to determine the best parent selection strategy on the basis of changing network conditions. The findings show that the suggested strategy significantly increases packet delivery ratio and average delay even with only a slight rise in signalling frequency. Compared with iCPLA, RPL-MRHOF's average delay is decreased by 27% and by 12% with the suggested method.

In 2021, Adil, M. [18] proposed a Dynamic hop selection static routing protocol (DHSSRP) for creating congestion-free infrastructures. The performance evaluation shows that the suggested scheme is considerably greater than the field-tested method in terms of traffic congestion, throughput, and network longevity. A 95.8% participation rate was recorded for a person's sensor devices in the network with the similar onboard battery power.

In 2021, Adil, M. et al. [19] presented a 3-tier enhanced ad hoc on-demand distance vector (enhanced-AODV) routing techniques for reducing congestion and distributing the load. By categorizing traffic with alternate routes, the enhanced-AODV protocol reduces energy consumption and increases device longevity. Simulation results show that their approach outperforms three other comparable approaches in terms of network lifetime, latency, and PLR by 15%, 17%, and around 10%, respectively.

In 2022, Grover, A. et al. [20] introduced a novel rate-aware congestion control (RACC) technique which establishes 3 levels of congestion on the basis of throughput, data rate, delay, and overhead. The proposed RACC method improves parameters such as throughput, PDR, and normalized routing overhead by 17%, 8.35%, and 0.56%. It also reduces MAC Overhead by 0.64%, average delay time by 2.04%, and average remaining energy by 592.8%, respectively.

In 2022, Kaviani, F. and Soltanaghaei, M. [21] proposed a technique called Congestion and QoS-Aware RPL for IoT applications (CQARPL) to reduce the congestion during routing in IoT. The experimental results indicate that the suggested technique preserves the transmission quality and manages congestion in IoT. The suggested protocol enables the ability to predict congestion and reduces its occurrence.

In 2021, Pushpa Mettilsha, J. et al. [22] proposed Reliable Path Routing (RPR) as a way to control congestion in a number of crucial IoT applications. A Node Selecting Factor (NSF) is calculated by the RPR protocol based on buffer occupancy and other parameters and is used to choose the Node for packet transmission. Simulated results clearly indicated that the RPR protocol reduced time by 38% and increased (packet delivery ratio) PDR by 7%, compared to SPR, SGEAR, CoAR, and CDTMRLB protocols.

In 2021, Shirbeigi, M. et al. [23] introduced CBR-RPL, a lightweight RPL-based routing strategy for congestion control. By routing packets via a unique drop-aware Objective Function (OF), the proposed method clusters the nodes logically and lowers congestion. According to the simulation results, CBR-RPL framework increases stability in the context of PDR by 38.2% and 75% when compared to RPL and QURPL.

In 2021, Chappala, R. et al. [24] proposed an Adaptive Congestion Window (ACW) technique for congestion control in IoT. In comparison to the IoT Congestion Control Algorithm (IoT-CCA) and the Improved Stream Control Transmission Protocol (IMPSCTP), ACW performed better in terms of PDR, throughput, and delay by 27.4%, 11.84%, and 33.75% compared to IoT-CCA, and by 44.1 percent, 22.6 percent, and 50% compared to IMP-SCTP, respectively.

In 2021, Magubane, Z. et al. [25] proposed a context aware and load balancing routing algorithm for RPL (ECLRPL) for balancing the load and prevent congestion in the IoT network. ECLRPL performed better on the Contiki OS than CLRPL when compared on PDR, delay, energy consumption, and Rt-Metrics. The ECLRPL delivered 65% of packets efficiently on a network of 10 nodes while consuming very little power.

There are numerous approaches in the literature that have been proposed to address this problem. However, most of these methods waste a lot of energy, provide poor service, and do not meet RPL standards. Additionally, the network can occasionally fail to deliver packets repeatedly. Currently, scientists are working to overcome this problem in IoT networks, either by developing new methods or modifying existing ones. In this paper, a novel Geodetic fuzzy subgraph-based ranking (GFSR-RPL) has been proposed for reducing congestion.

3 GEODETIC FUZZY SUBGRAPH-BASED RANKING FRAMEWORK

In this section, a novel geodetic fuzzy subgraph based ranking framework has been proposed for reducing congestion in RPL networks. Initially, the nodes are clustered using K-means clustering technique, then the clustered nodes are passed through a three major steps, namely, RTT estimator, RTO adjustment and Geodetic fuzzy subgraph which will rank the nodes. The overall block diagram of the proposed GFSR-RPL method has been given in Fig. 1.

3.1 Clustering of Nodes

The nodes in RPL are clustered by employing k-means clustering technique. K-means algorithm is based mainly on the Euclidian distances and clusters the nodes depending on distance between centroids and datapoints. During k-means clustering, the number of clusters is assumed to be constant. Initialize one of the m input patterns $(n_1 \dots n_m)$ with one of the k prototypes $(p_1, p_2 \dots p_k)$. Therefore,

$$p_s = n_q, s \in \{1, \dots, k\}, q \in \{1, \dots, m\} \tag{1}$$

In order to determine the node in the band with the closest center, the algorithm calculates the shortest distance between the k centers and the sensor. The algorithm is terminated when the group reaches stability. The algorithm determines the new center of gravity for each band.

Minimizing an objective function known as a squared error function by:

$$S(J)=\sum_{x=1}^{d}\sum_{y=1}^{d_x}\left(\left\|W_x-U_y\right\|\right)^2 \tag{2}$$

where, $\left(\left\|W_x-U_y\right\|\right)^2$ represents the Euclidean distance between w_x-u_y. d_x is the number of data points in x^{th} cluster and d_y is the number of cluster centers.

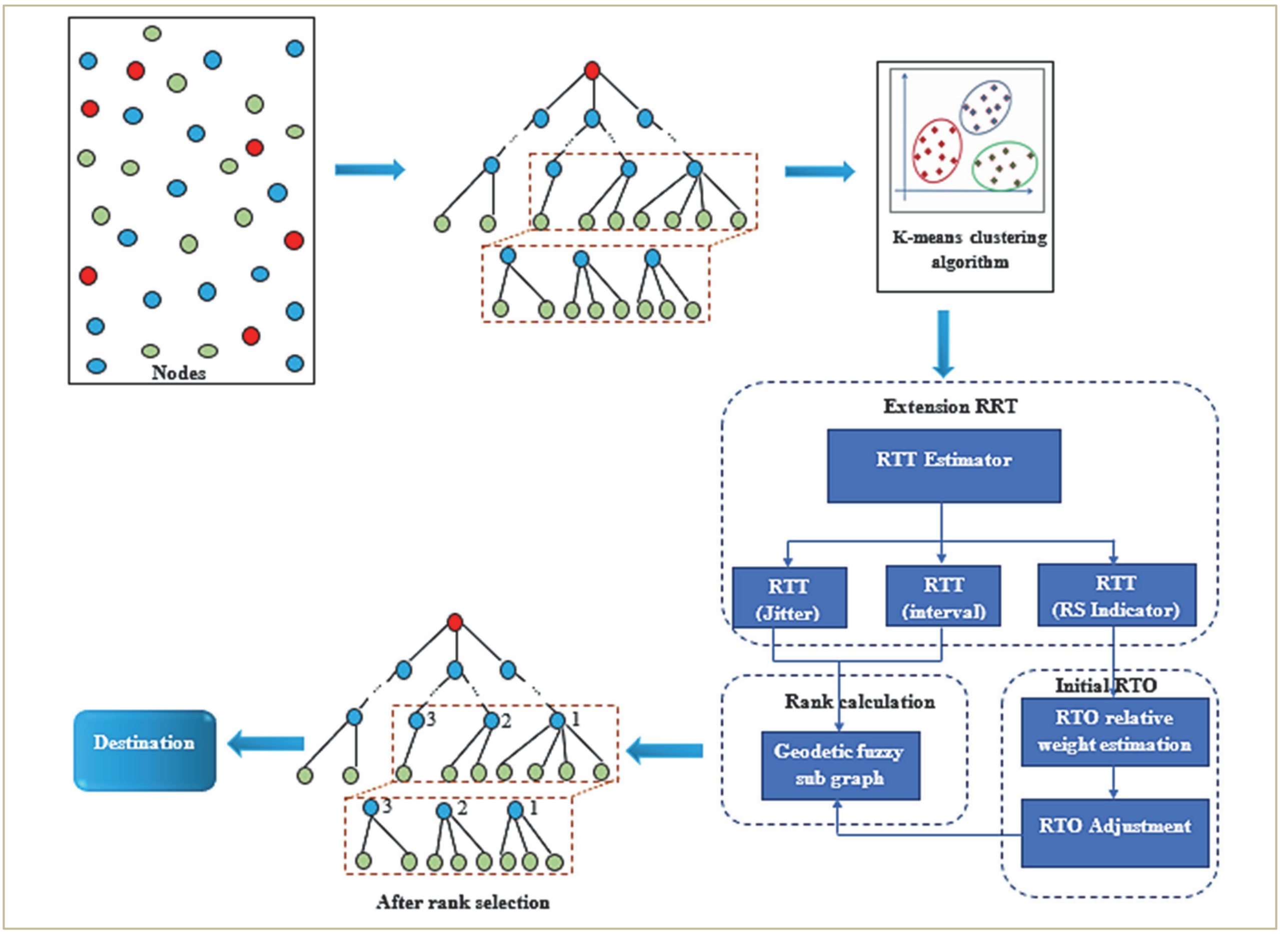


Figure 1 Overall block diagram for the proposed GFSR-RPL framework

Algorithm: Pseudocode of K-means

Initialize '*k*' centroids at random locations for clustering the nodes.

Calculate the Euclidian distance between the node and the closest centroid and assign.

Recalculate the centroids' positions in each cluster and check for differences.

Proceed to step 2, if any position change of centroid occurs else clusters are finalized.

End the process.

3.2 Ranking via Geodetic Fuzzy Subgraph Method

Using the proposed technique, retransmissions could be significantly reduced, minimizing energy usage and improving network performance in terms of throughput and latency.

3.2.1 RTT Estimator

This step involves building *RTT* estimator variables. These parameters are *RTT* Jitter, *RTT* Interval, and *RS* Indicator. These factors are used in both the original *RTO* configuration and the Geodetic Fuzzy subgraph to estimate congestion circumstances in an unrealistic way. This individual variable is described in detail and analyzed.

3.2.2 RS Indicator

To calculate the *RS* indicator, the concept of relative strength was adapted to establish the relationship between a small and a large value over some period of time. Time-series data can be analysed using the *RS* indicator to determine where two datasets diverge. Using the following formula, the relative strength can be calculated:

$$RS=\frac{\operatorname{avg}\left(RTT_{\mathrm{s}}\right)}{\operatorname{avg}\left(RTT_{\mathrm{w}}\right)} \tag{3}$$

According to Eq.(3), the relative strength of the *RTT* (RTT_{w}) is determined by the average ratio between *RTT* weak (RTT_{w}) and *RTT* strong (RTT_{s}). For calculation of the *RS* indicator, Eq. (4) uses the resulting *RS*.

$$RS_{\text{ind}}=100-\left(\frac{100}{1-RS}\right) \tag{4}$$

The RS_{ind}($RS_{indicator}$) falls between 0 and 1, and RS is a temporal average which illustrates the correlation between RTT_s and RTT_w. RS_{ind} is employed as an auxiliary variable in the RTO estimation.

3.2.3 RS Interval

On the end node (server node), this variable measures RTT consistency over time. In determining the geodetic fuzzy subgraph system, network utilization is assumed. RTT Interval is calculated using the total number of ACK packets received from the start of transfer of data until new transmission happens in the RTO round.

3.2.4 RTT Jitter

Transmission delay instabilities or variations are measured by this parameter. Hence, jitter indicates the likelihood of congestion at the end node as a result of concurrent network demand. Each packet received by the client node is acknowledged by the server node within a regular round-trip time [10]. A destination node that is overloaded, however, needs more time to process incoming packets when there is congestion, resulting in an irregular RTT and acknowledgement time. This irregularity caused by node congestion is known as jitter. The RTT Jitter is characterized by

$$RTT_{J} = \left| RTT_{K-1} - RTT_{k} \right| \tag{5}$$

Absolute variances in delay between the RTT_s, such as RTT_k and RTT_{K-1} are used to indicate the RTT jitter. The congestion for the Geodetic Fuzzy subgraph is then determined using the resulting RTT_J parameter.

3.2.5 Initial RTO

The purpose of this section is to present methods for determining the initial RTO and modifying the RTO properly employing RTT Trend Evaluation and relative weights, respectively. Based on earlier studies on pattern prediction, the initial RTO estimation is generated. The following provides an explanation of estimates for the initial RTO and its trend.

3.2.6 RTO Relative Weight Estimation

In the enhancement, the relative strength indicator, as specified in the RTT estimator, is used to modify the ratio of strong to weak. In this way, the initial RTO can be predicted by Eq. (6).

$$RTO_{e} = RS_{ind} \times RTO_{w} + \left(1 - RS_{ind}\right) \times RTO_{s} \tag{6}$$

Based on the resulting RTO_e, the following subsection provides a calculation.

3.2.7 RTO Adjustment

The difference between consecutive RTT_s, i.e., k and k – 1, is referred to as the RTT Trend which is given in Eq. (7).

$$RTT_{tr} = RTT_{K-1} - RTT_{k} \tag{7}$$

The generated RTT_{tr} is employed as a parameter in the Geodetic fuzzy subgraph-based ranking as well as to estimate the future trend as given in Eq. (8).

$$F_{tr} = F_{k-1} + RS_{ind} \times \left(RTT_{tr} - F_{k-1} \right) \tag{8}$$

In Eq. (9), the resulting prediction is employed to adjust the initial RTO (RTO_{in}).

$$RTT_{in} = RTO_{e} + F_{tr} \tag{9}$$

where RTO_e are the initial RTO adjustment (RTO_{in}) and that assessed through the relative weight approach. The FT_{tr} is the trend predicted by Eq. (9).

3.2.8 Geodetic Fuzzy Subgraph

The geodesic number for a fuzzy graph is developed by Suvarna and Sunitha by using Bhutani and Rosenfeld's geodesic distance concept. For the purpose of calculating the rank of a subgraph, this section presents a minimum geodetic fuzzy subgraph.

An arc (u, v) is considered strong if its weight is greater than the strength of connectivity between its end nodes (u, v). The path P is considered to be strong if it consists exclusively of strong arcs. A u-v geodesic is a reliable route P from u to v, and its length is represented by the geodesic distance between u, v, and $dg(u, v)$. In a connected fuzzy graph G: (V, σ, μ), the geodesic eccentricity $ecc(u)$ of a node is represented by the formula by $ecc(u) = \max_{v \in V} dg$ (u, v). G-peripheral nodes or diametral nodes are nodes with the greatest $ecc(u)$.

Geodesics with maximum geodesic distances are called diametral paths, and their maximum distances are called diameters [11]. Geodesic basis order for a fuzzy graph, $gn(G)$, is G: (V, σ, μ), and it represents the geodesic number for the fuzzy graph which is shown in Fig. 2.

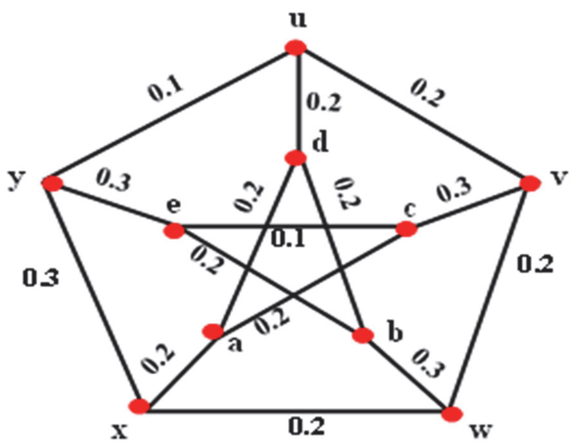


Figure 2 Fuzzy graph G

The arc (u, y) in this instance is δ-arc, while all other arcs are strong. Thus, $dg(u, y) = 4$ with $u - d - a - x - y$, $u - d - b - e - y$, $u - v - c - e - y$ and $u - v - w - x - y$ as the $u - y$ geodesics. Hence $ecc(u) = \max\{dg(u, v)/v \in V\} = 2$, $ecc(v) = 2$, $ecc(w) = 2$, $ecc(x) = 2$ $ecc(y) = 2$ $ecc(a) = 2$, $ecc(b) = 2$ $ecc(c) = 2$ $ecc(d) = 2$ and $ecc(e) = 2$.

In a complete fuzzy network, the arc is the geodesic among its end nodes. Therefore, a complete fuzzy graph's node set is its only geodesic cover [12]. The fuzzy end nodes of a fuzzy tree form a distinct geodesic basis. Clearly, G is a subgraph of H that displays geodetic fuzzy information. The arc (u, y) in graph G, is a δ-arc and so $dg(u, y) = 4$ with $u - d - a - x - y$, $u - d - b - e - y$, $u - v - c - e - y$ and $u - v - w - x - y$ are the geodesics of this graph.

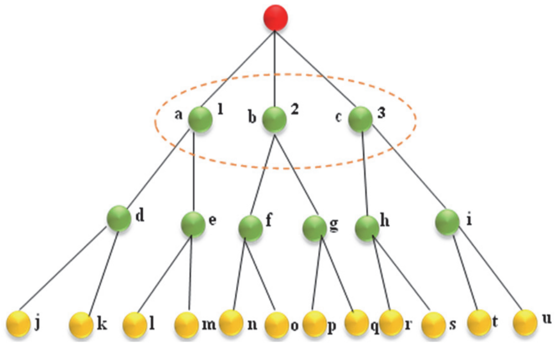


Figure 3 DODAG of RPL network

Fig. 3 expresses the DODAG of RPL network, in which the geodetic number need to be calculated for rank calculation. Let us assume the tree as T with n nodes. Initially, the geodesic of the tree should be calculated by computing the eccentricity of nodes, after the root node. Then, nodes a, b and c are considered for calculating rank. So, the eccentricity of node a i.e $ecc(a) = 4$, $ecc(b) = 4$ and $ecc(c) = 4$ and the geodesic number of T, $g(T) = 4$. Then the 1st node a will be chosen for further process.

Next the subgraph of the node a is taken for calculating rank, which is depicted in Fig. 4. The subgraph of a has been considered for calculating eccentricity. The eccentricity of node d i.e $ecc(d) = 5$ and $ecc(e) = 5$. And then the node d is chosen and so on. Thus, the ranking for the nodes has been calculated and routes the packets to the destination.

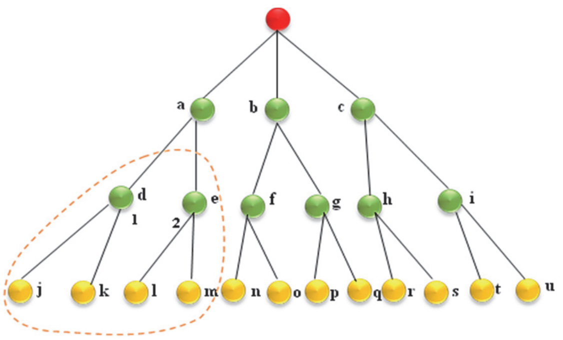


Figure 4 Rank calculation for subgraph

5 RESULTS AND DISCUSSION

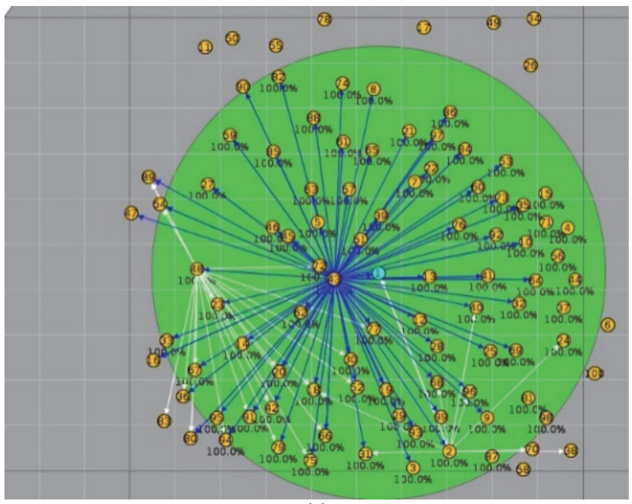
Simulations were performed to demonstrate effectiveness and performance of GFSR-RPL, and the results were compared to those of existing approaches discussed in the related studies section. They were RPR [22], CBR-RPL [23], ACW [24] and ECLRPL [25]. The performance evaluation is done in terms of several parameters as energy consumption, latency, PDR, throughput and packet overhead. The simulation parameters for the proposed GFSR-RPL are showed in Tab. 1.

Table 1 Simulation parameters of GFSR-RPL technique

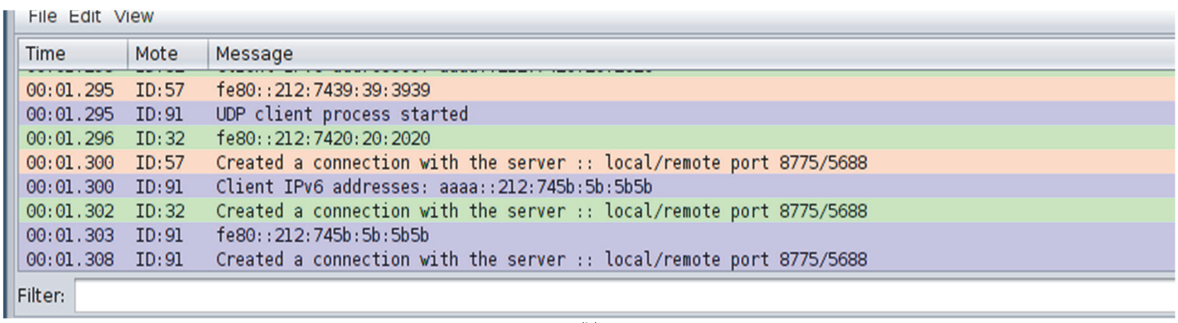
Simulation parameters	
OS	Contiki 2.7
Network simulator	Cooja
Number of nodes	100
Simulation area	100m×100m
Duration for each simulation	1200000ms
Hardware platform	Sky mote

5.1 Performance Evaluation

The performance of GFSR-RPL is assessed using simulations in the following section. GFSR-RPL was implemented in ContikiOS3.1. Cooja motes are used to simulate wireless sensor devices. Communication technology IEEE 802.15.4 and radio duty cycling (RDC) deactivation are used in the simulations [13]. The network consists of 100 nodes arranged in concentric circles. The network topology is constructed using the RPL routing protocol. Fig. 5a and Fig. 5b display the results in the network window.



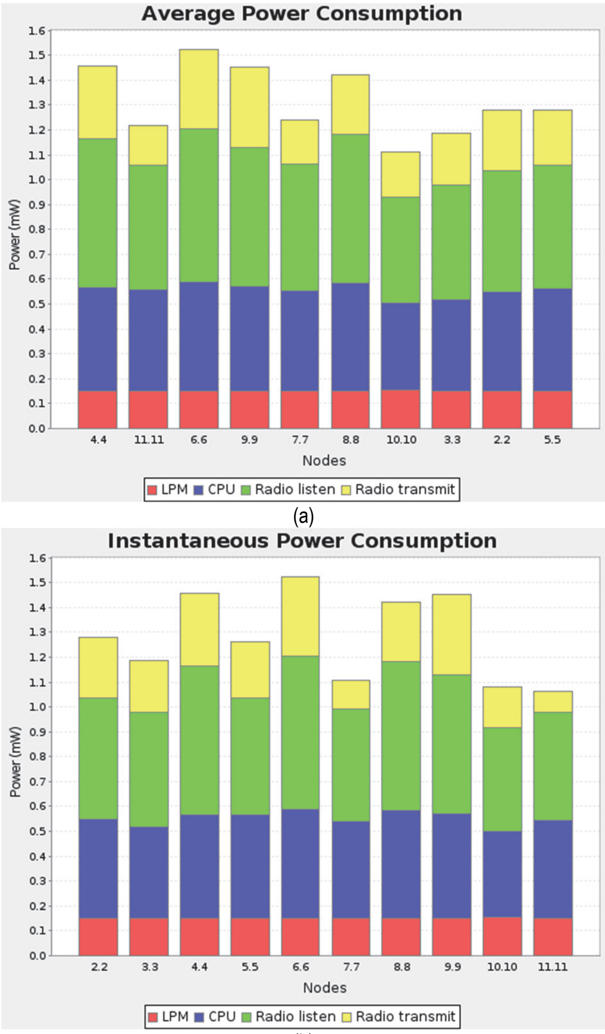
(a)



(b)

Figure 5 Network simulator window with 100 nodes

When network density increases, packet loss and power consumption increase due to congestion. Consequently, traffic load balancing opportunities in the network are reduced.



(b)

Figure 6 Power consumption of nodes

The average power consumption of nodes is shown in Fig. 6a. In each sensor node, power consumption $\left(Pow_{\text{Avg}}\right)$ is the sum of energy consumption in the *CPU* state, the Low Power Mode state (*LPM*), which is activated when the sensor node enters *LPM*, the radio listen mode, and the radio transmit mode. Fig. 6b shows the instantaneous power consumption of nodes [14]. To determine the energy consumption in each state, the number of *CPU* ticks on the basis of microcontroller, the current power consumption, and the battery voltage are considered. For the purpose of computing the power consumption of each node, the following formula is used:

$$Pow_{\text{Avg}} = CPU + LPM + Rad_{\text{listen}} + Rad_{\text{transmit}} \tag{10}$$

Fig. 7 depicts the ARDC for node 100. This radio duty cycle is employed to estimate the total number of packets that this node sends and receives. The radio duty cycle is widely used in MAC layer. If the transceiver is off, the node cannot send or receive messages. Therefore, nodes must set up the radio so that they can receive messages while keeping the radio off between source nodes and route nodes [15]. Sending and receiving data consumes energy, as shown in the graph. In a time-synchronized network, the nodes have a schedule that specifies when each node must communicate. A protocol would turn on the radio at a certain point, allowing packets to be sent between nearby nodes.

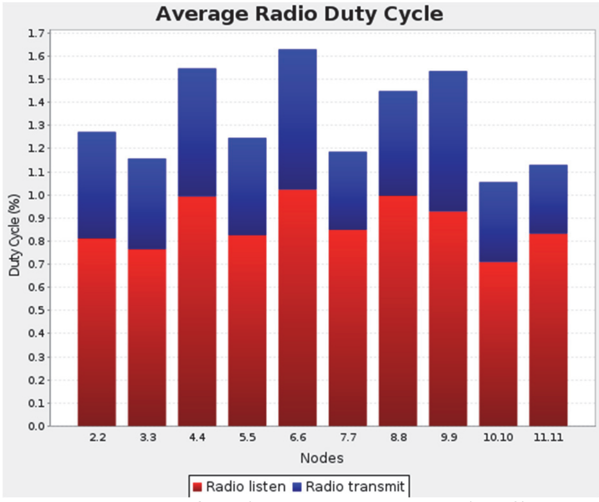


Figure 7 Graph for average radio duty cycle (ARDC)

Fig. 8 shows the number of network hops per node for the RPL routing protocol. Based on the graph above, each node must make a certain number of hops before reaching the root node. As the yield increases, the number of hops will increase. A certain number of packets must be forwarded to the next hop in order to reach the root node. Next hop routing can also reduce the size of the routing table.

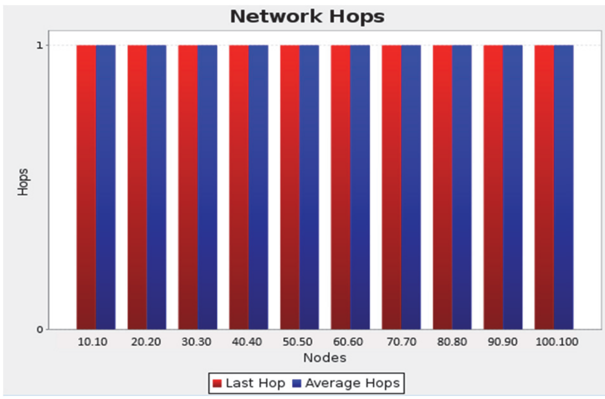


Figure 8 Network hops per node

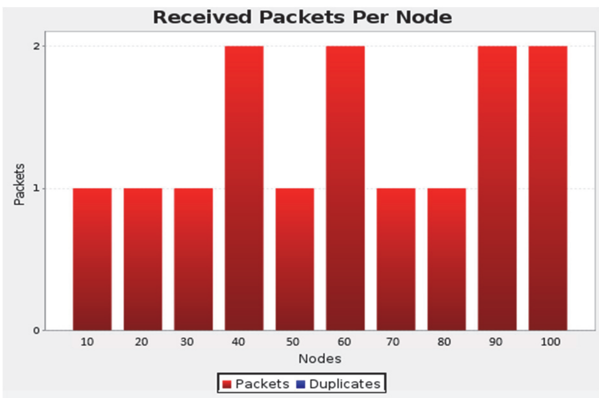


Figure 9 Received packets per node

Fig. 9 shows that 457 packets were received, and zero packets are estimated to have been lost. It appears that the RPL performs well after completing the DODAG routing scenarios.

5.2 Comparative Analysis

The performance of existing methods was examined to demonstrate that the result of the proposed framework is more efficient. The comparative analysis is performed between the suggested GFSR-RPL technique and the four existing methods such as RPR [22], CBR-RPL [23], ACW [24] and ECLRPL [25].

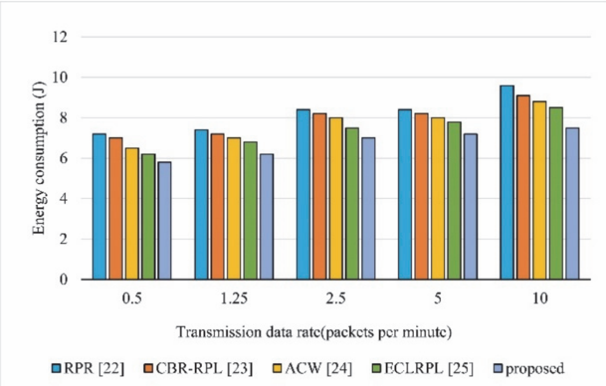


Figure 10 Comparison of energy consumption

The energy consumption of the suggested GFSR-RPL method with existing systems such as RPR, CBR-RPL, ACW and ECLRPL techniques is depicted in Fig. 10. According to network congestion and decreased distances between nodes, the average energy consumption decreases as the number of nodes increases. The proposed GFSR-RPL method reduces the energy consumption of 43.58%, 25.8%, 14.82% and 6.85% than existing methods such as RPR, CBR-RPL, ACW and ECLRPL due to the energy metric and number of children.

Fig. 11 depicts the routing overhead (RO) for the nodes. For the purpose of assessing the effectiveness of GFRS-RPL routing, RO is a crucial factor. According to this figure, the proposed RO offers superior performance to the existing methods, including RPR, CBR-RPL, ACW, and ECLRPL.

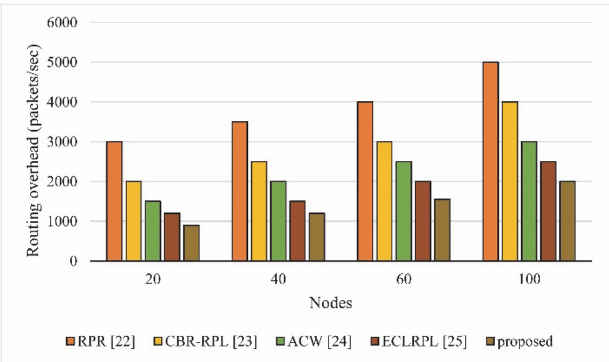


Figure 11 Comparison of routing overhead

Fig. 11 depicts the routing overhead (RO) for the nodes. For the purpose of assessing the effectiveness of GFRS-RPL routing, RO is a crucial factor. According to this figure, the proposed RO offers superior performance to the existing methods, including RPR, CBR-RPL, ACW, and ECLRPL.

5 CONCLUSIONS

This research presents a novel Geodetic fuzzy subgraph-based ranking (GFSR-RPL) congestion control scheme for RPL. The proposed method selects the cluster head using K-means clustering. Then the rank calculation can be done via the final route setting for data transmission. An estimator of Round-Trip Time (*RTT*) considers many features of congestion conditions, a method of rank computation based on geodetic fuzzy subgraphs, and an accurate prediction of initial retransmission timeouts. The simulation has been performed in cooja simulator. The proposed system reduces the energy consumption of 43.58%, 25.8%, 14.82% and 6.85% when compared with existing methods such as RPR, CBR-RPL, ACW and ECLRPL due to the energy metric and number of children. We intend to fully implement the proposed approach in the future to evaluate its performance. Additionally, we are focusing on the energy utilisation in MicaZ and Tmote Sky from a computer perspective.

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