Enhancing RPL using E-MOF: a fuzzy-based mobility model for IoV

Sakshi Garg[a], Deepti Mehrotra[b]*, Hari Mohan Pandey[c], Sujata Pandey[d]

***Abstract*— Routing Protocol (RPL) is treated as a standard protocol for Low power and Lossy Networks (LLNs). It was introduced by the Internet Engineering Task Force (IETF) Routing over Low Power and Lossy network (ROLL) working group to deal with routing challenges that occur in LLNs. It is noted that RPL permits optimization at several levels in the networks. RPL uses an objective function that helps in evaluating network performance. The objective function can be created using single or composite metrics. Literature reveals that single metrics-based objective function showed poor performance whilst composite metrics have demonstrated excellent performance, but still there is plenty of scope for further improvement. This paper shows an extension of the composite metrics. The real problem of RPL concerning IoV is that the heterogeneous network undergoes extreme packet loss and congestion which disables the full utilization of network capacity. Thus, this paper presents an enhanced fuzzy-based objective function and analyzes its impact on the Internet of Vehicles (IoV) network. The objective function aims at reducing the Control Traffic Overhead (CTO) in the network and providing a high Packet Delivery Ratio (PDR). The contribution of this paper is as follows: First, network scalability is analyzed for (a) random and grid configurations; (b) random and Self-similar Least Action Walk (SLAW) mobility models. Second, the performance of the proposed E-MOF is validated with the standard objective functions for both networks. Third, extensive computer simulations are performed for performance analysis. Simulation result reveals that the proposed E-MOF outperform OF-EC concerning the PDR, CTO and comparable latency at the expense of high energy consumption for both configurations and mobility models. Finally, it is remarked that E-MOF extends the applicability of the RPL for IoV networks. Further, it commits a better PDR Quality of Service (QoS) and high network reliability. The results and discussion reported in this paper are outstanding, therefore, they will motivate other researchers to develop a novel approach in the future.**

***Keywords*— Low power and Lossy Networks, RPL, Objective Function, ETX, Hop Count, QoS.**

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I. Introduction

The idea of associating a smart object to the web remains the essential objective of the Internet of Things (IoT) [1]. IoT is answerable for the correspondence among various objects that use sensors/motes. These motes are usually battery driven and more obligated to visit energy exhaustion [2]. The boisterous channels and asset limitations lead to low power and lossy network in IoT deployment. Along these lines, to resolve this issue RPL convention was presented in 2012 by the IETF ROLL working group [3]. RPL is genuinely adaptable to permit topology changes [4][5] and helps in simulating real scenarios. RPL utilizes an objective function to decide the best parent and in this manner, an ideal way for the construction of Destination Oriented Directed Acyclic Graph (DODAG). The objective function depends on either a single metric or composite/additive metric. Though, because of impediments of single metric when contrasted with composite metric [6][7], optimizing the additive metric is the cutting-edge interest area for the researchers [8][9][10].

The brought impact of IoT on vehicular networks [11][12] and transportation [13] provoked the improvement of through and through another field called the Internet of Vehicles (IoV) [14][15]. The real concern of RPL for IoV networks is to establish an arrangement that ensures maximum utilization of the network with a high Packet Delivery Ratio (PDR) and low or negligible congestion. A few researchers [16][17][18] have targeted these concerns but they remain an open issue to date. This motivated us to propose an objective function which can mark these problems for IoV networks essentially. The proposed objective function is based on fuzzy logic with additionality of mobile nodes. Besides, the drive of these mobile nodes is grounded on mobility models. Thus, the thought behind this paper is to progress and upgrade the utilization of RPL protocol from IoT network to IoV network with the aim to intensify Packet Delivery Ratio (PDR) and condense the network congestion in order to provide better network utilization.

Nevertheless, one can find many ongoing pieces of research related to RPL which have proposed enhancements by optimizing objective function [19][20], introducing mobility [21][22][23][24], performance evaluation using real experimentation [25][26][27], etc. but primarily for IoT network [28]. RPL for the IoV network hasn't been much accentuated. This gap is covered in our paper as we provide an **E**nhanced fuzzy-based **M**obile **O**bjective **F**unction: **E-MOF** and analyze its performance for IoV networks using mobility models. This upgrade will work on the longevity and functionality of the RPL protocol. The acknowledgement of this idea in the real IoV network can be perceived in the applications like Traffic Monitoring System (TMS), Smart Parking, Electronic Toll Collection (ETC), Advanced

Metering Infrastructure (AMI), and so forth. Subsequently, this paper proposes the utilization of distinctive objective functions for IoV networks, which were proposed for IoT networks only.

The principal contributions of this paper are highlighted as:

- First, we present a mobile fuzzy-based routing metric (E-MOF) which takes energy consumption by nodes, hops count per node and estimated transmissions per link into account to provide better network Quality of Service (QoS).
- Second, network scalability is analyzed for E-MOF and OF-EC for IoT and IoV networks. The outcomes legitimize the utilization of E-MOF for both networks.
- Third, the two objective functions are analyzed for two configurations (random and grid) and two mobility models (random and SLAW). It is noticed that E-MOF showed a high Packet Delivery Ratio (PDR), low Control Traffic Overhead (CTO) and comparable latency to OF-EC.

The discoveries show that E-MOF is better than OF-EC and recommends the utilization of the proposed E-MOF with grid configuration for the static environment and SLAW mobility model for the dynamic environment. The results of this study will benefit the breeding researchers in this domain to propose an even better solution to the real problem of heterogenous IoV networks discussed in this article.

The rest of the paper is organized as: Section II presents an RPL outline and related works within the extent of this paper. Section III examines the proposed model by defining the problem statement and proposed solution. Section IV gives the simulation details and outcomes of this analysis. Ultimately, Section V apportions the conclusion of this study. An appendix is also included last to refer to abbreviations used in this paper.

II. Literature Study

RPL acquired prominence among researchers in the wake of being presented as an answer for LLN issues [29]. RPL uses an objective function for the construction of DODAG. DODAG exchanges control messages for the establishment of the network. There are four control messages DODAG Information Solicitation (DIS), DODAG Information Object (DIO), Destination Advertisement Object (DAO) and Destination Advertisement Object Acknowledgement (DAO-Ack). The control messages are exchanged as shown in Fig.1. This attracted researchers [30][31][32] to work on the optimization of the RPL objective function to select the best parent and optimal path for the construction of DODAG.

Authors in [33] optimized the network using a single node metric (remaining energy) instead of a single link metric, but the results improved at the cost of link quality. Consequently, the use of a single metric was not sufficient to optimize the network. Also, the dynamic environment using RPL was not taken into consideration for IoT networks. In [34], the authors considered mobile base stations. The metric was based on fuzzy logic using distance from the sink, energy sensor and cluster-centric priority as parameters. They aimed to reduce energy consumption. However, improvement in the network lifetime with the mobile base station doesn't replicate the real dynamic scenarios of the IoV network.

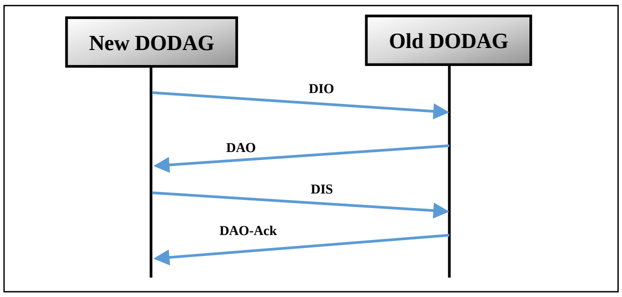


Fig. 1. DODAG Control Message Structure

Paper [35] also proposed a new objective function based on fuzzy logic that combined Expected Transmission Count (ETX), Hop Count (HC), end-to-end delay and network lifetime metrics. But, the proposal was only compared to the standard RPL objective functions and only for a static IoT environment. In [36], the authors proposed a new fuzzy-based objective function considering composite metrics. Their results were effective when compared to standard objective functions and other proposed objective functions in the literature. But, the results were tested only for static nodes for IoT networks, which is extended to mobile nodes for the IoV network in this article.

Since then, many articles have been published with optimized objective functions for the static network but very few have worked on the mobile nature of the RPL. Likewise, the authors in [37] proposed an objective function considering ETX, content and energy using a trickle timer to optimize the RPL network for IoT applications. Their results were effective but only for static nodes. Likewise, in the paper [38] authors presented a fuzzy supervised learning approach for optimal path selection for IoT networks. They considered Received Signal Strength Indicator (RSSI), remaining energy and queue utilization as composite metrics. Still, the mobility of nodes was missing. A significant level of studies was discovered featuring the difficulties and limitations of RPL [46][47] while some proposed that the objective functions are dependent on composite measurements for static RPL for IoT networks.

Although some studies have covered IoT, mobile IoT (the works that didn't consider RPL for vehicular networks but the nature of the network is dynamic), IoV and all are listed in Table 1. Our superiority of work over theirs is also discussed in the table. But, scenarios that make use of mobile nodes for IoV networks are still to be covered. Hence, this paper focuses on extending the use of the RPL protocol for the IoV network.

Table 1. Differentiation of related studies with the proposed methodology

S. No.	Related Study	Considered Metrics	Methodology	Network	Evaluated Metrics	Cons	Our uniqueness	Year
1	[33]	Remaining energy	Energy aware routing	IoT	Link quality	No mobility	Composite metrics considered, Mobility incorporated	2013
2	[34]	Distance, motes energy	Fuzzy based	IoT	Energy Consumption, network lifetime	No justification for real scenarios	Application to real scenarios with better PDR	2013
3	[35]	ETX, HC, end-to-end delay	Fuzzy based	IoT	Network lifetime	Only compared to standard objective functions	Compared to standard and already proposed objective functions also.	2015
4	[36]	ETX, HC, energy	Fuzzy based	IoT	PDR, overhead	No mobility	Mobility considered	2017
5	mRPL+ [24]	Packet loss, delay, mobility	Combination of two hand-off models	Mobile IoT	PDR, disconnection period	No comparison with existing studies and no consideration of mobility models	Comparison with existing works and mobility models considered	2017
6	[37]	ETX, content, energy	Trickle timer	IoT	PDR, delay, overhead	No mobility	Mobility considered	2020
7	[22]	mRPL [41]	Firefly optimization	Mobile IoT	PDR, EC, Hop count, end-to-end delay	Consider only random mobility	Considered two mobility models to study its impact on the network	2020
8	MARPL [23]	RSSI, mobility	Cross-layer approach	Mobile IoT	PDR, EC, low overhead	No comparison of mobility models	Considered Mobility models	2020
9	FSS [38]	RSSI, remaining energy, queue utilization	Fuzzy based	IoT	Quality node prediction	No mobility	Mobility considered	2021
10	ARMOR [21]	Time to reside, mobility	Mobility aware routing metric	IoV	Reliability, connection period of motes	Power consumption was kept constant and random mobility is only considered	Power consumption is also targeted and mobility is observed for two mobility models	2021
11	[51]	ETX, EC, mobility	Multiple sinks, multiple	IoT and IoV	PDR, ETX	Mobility is incorporated using	Its findings are used to justify the	2021

			topologies, hybrid model			mobility models	use of the two considered mobility models in this study	
12	RPL-OC [26]	Distributed energy, end-to-end paths, mobility	Operator calculus approach	IoT	End-to-end delay, energy consumption	No mobility models are considered with low PDR	Mobility models are considered with high PDR	2022
13	EMBOF-RPL [39]	RSSI, mobility	Echelon approach	Mobile IoT	Detection accuracy, isolation latency, PDR, EC	Rank attack detection for security of IoT network	Composite metric to optimize network performance for IoT and IoV networks both.	2022
14	V-RPL [40]	Speed, ETX, delay, mobility	Multi-criteria decision making	Mobile IoT	PDR, end-to-end delay, energy consumption	Better than mostly proposed solutions (mRPL [41], EMA-RPL [42], Co-RPL [43], E-Trickle [44]) for mobility but didn't consider any specific mobility model to justify the motion of motes	Better than the existing works and mobility models are also taken into consideration	2022
15	MSAT-RPL [45]	Speed, time, location,	Trickle algorithm	IoV	PDR, energy consumption, end-to-end delay, overhead	Standard objective function is only used to study the impact of proposed changes in trickle algorithm	Results are compared with the existing work and standard objective functions also	2022

III. Problem Statement and Proposed Model

A. Problem Statement

The advancement in optimizing the objective function of RPL for IoT networks is manifold. The current need to establish decent communication for the IoV network is a rising concern. As of now, RPL is only used for IoT network communication and very few studies have targeted mobile IoT networks and countable studies on IoV network communication. The snag is to establish communication for a heterogeneous IoV network that ensures full network capacity utilization with low congestion and high PDR.

Scenario: The instance where Road Side Units (RSUs) are fixed i.e. static and the vehicles with On Board Units (OBUs) are moving i.e. dynamic/mobile. This type of Vehicle-to-Infrastructure (V2I) [48] communication can be easily managed through RPL protocol, without the need to develop a new protocol altogether.

The Smart City concept can provide a better understanding of the above scenario as shown in Fig. 2. This figure shows the random movement of vehicles from all four directions and pedestrian movement which also confers mobile nodes with OBUs. These are considered in this study using the random mobility model and SLAW mobility model respectively. The traffic control centre, traffic lights, roadside cameras, automated parking system, etc. represents static nodes with RSUs. Further, these communicate with each other using a network protocol and vehicular cloud, thus forming a vehicular network. Since this dimension of RPL protocol has not been tested and explored yet, thus this paper presents the extension of RPL protocol using a mobile fuzzy-based objective function considering composite metrics for the IoV network.

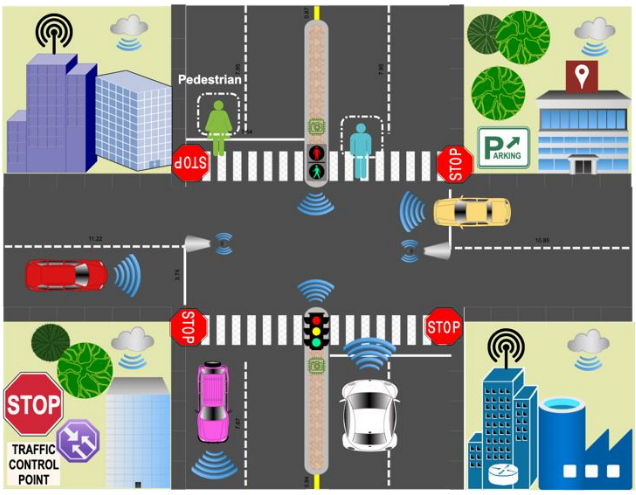


Fig. 2. Smart City Scenario

B. Proposed Model

The proposed model makes use of mobile nodes to establish an IoV network instance. The E-MOF is computed using ETX, Energy Consumption (EC) and HC as combined metrics. The fuzzy process takes two input variables and converts them into a single output variable. This is mainly a four-step process as shown in Fig. 3.

The linguistic variables are chosen for the fuzzification process. Here, EC and ETX are chosen as linguistic variables. The EC input and ETX input are (low, average, high) and (small, average, long) respectively. The trapezoidal membership function distribution is used to estimate fuzzy values for both inputs [49]. Further, the link quality of the path is estimated using the Mamdani model [50]. The quality value is then, reflected by the linguistic variables: very bad, bad, average, good and very good. These values are further de-fuzzified to return a unique output value.

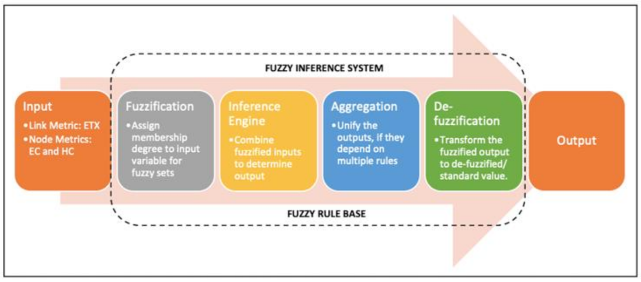


Fig. 3. Fuzzy logic process

The fuzzy rule base for EC and ETX is obtained as:

Rule Base 1. Fuzzy Rules for estimating EC and ETX

1. **Very good** = (low EC **&&** small ETX)
2. **Good** = (high EC **&&** average ETX) || (average EC **&&** small ETX)
3. **Average** = (low EC **&&** long ETX) || (average EC **&&** average ETX) || (high EC **&&** small ETX)
4. **Bad** = (average EC **&&** long ETX) || (high EC **&&** average ETX)
5. **Very bad** = (high EC **&&** long ETX)

The path quality can be estimated using EC and ETX membership functions.

$$average(path\_quality) = \max\ \{(\min\ (high(EC), small(ETX)),\ \min\ (average(EC), average(ETX)),\ \min\ (low(EC), long(ETX))\} \tag{1}$$

The lower the value of EC and ETX, the better the path route. These values are then used for defuzzification to provide a unique output value. The mathematical formula to obtain domain value R for defuzzification is given as:

$$R = \frac{\sum_{i=1}^{N} Wi\ \times\ \mu A\ (Wi)}{\sum_{i=1}^{N} \mu A\ (Wi)} \tag{2}$$

Where N is the number of rules initiated from the inference engine, Wi is the domain value concerning rule i and μA (Wi) is the predicate truth of that domain value.

Further, this fuzzy-based objective function is used to determine the best parent for the selection of the optimal path to build DODAG. The selection of the best parent is based on the calculation of rank which is obtained from the above fuzzy logic metric.

An instance of how the rank is allocated to the nodes in a DODAG construction for a random topology in an IoT network is depicted in Fig. 4. However, the nodes are mobile in the IoV network, because of which this rank assignment also changes with the change in DODAG construction. The rule base helps to retrieve the values for ETX and EC metrics which is further applied to calculate the best parent as shown in Fig. 5. The best parent is selected using Algorithm 1.

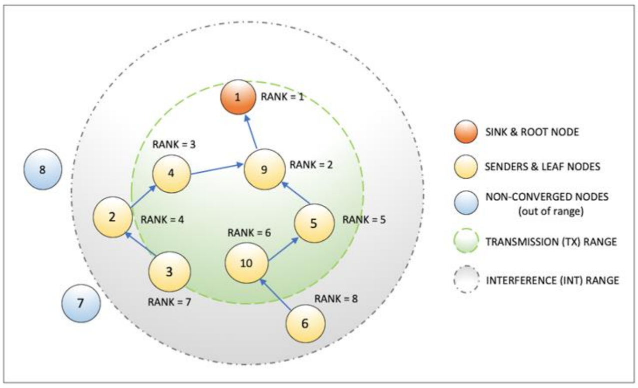


Fig. 4. Instance of rank allocation to nodes in random IoT network`

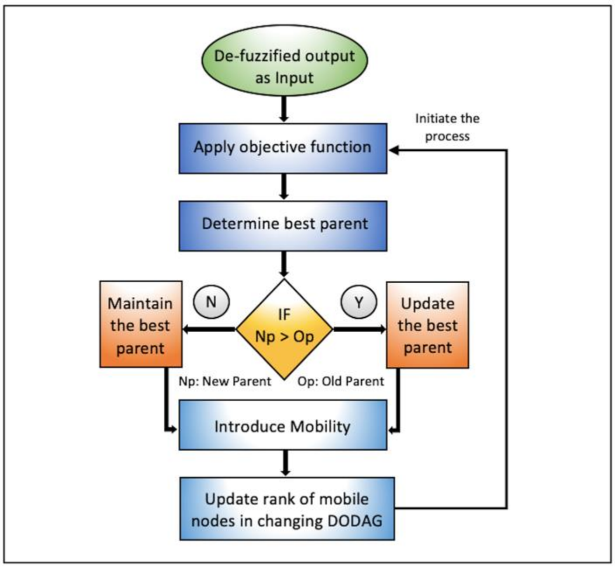


Fig. 5. Rank calculation by determining the best parent using E-MOF

Algorithm 1. Parent Selection Algorithm using composite metrics

Require: Input variables ETX, EC, HC, parent, batterycharge
Ensure: Nodes are updated with the routing metrics and new OCP is defined

```
if FUZZY {
    if parent = NULL                /* ETX calculation*/
        return (maximum ETX)
    else if (parent = ∑ (recent ETX + neighbors' ETX))
        return (parent)
    end if
    if parent = NULL                /*EC calculation*/
        return (batterycharge)
    else if (EC = recent EC) {
        parent = ∑ (batterycharge + recent EC)
        return (parent) }
    end if
    if parent = NULL                /*HC calculation*/
        return (maximum HC)
    else {
        HC = parent + 1
        return (HC) }
    end if
        return (quality (ETX, EC, HC)) }
end FUZZY
```

Thereafter the selection of the best parent based on OF-EC, the enhancement to this logic is introduced by introducing mobility in nodes referred to as E-MOF. The mobility in nodes is initiated by the *positions.dat* file which has four inputs: node, x position, y position and time. Now, the IoV scenario is reinstated with mobile nodes. The mobility of nodes is again established on two grounds: Random and SLAW. Random positions for nodes can be entered manually as well. But, positions for the SLAW mobility model can be generated using the BonnMotion tool. Although, the tool generates a *.wml* file which further needs to be converted to a *.dat* file by a wml-to-dat converter for actual use and implementation. The command to execute mobile positions of nodes using the SLAW model is:

$$./bm - f\ Test1\ \ SLAW - d3600\ \ - p20 - x100 - y100 - n10 - w6\ \ - r10$$

where f is the filename, d is the duration, p is the minimum pause time, x,y are boundaries, n is the number of nodes, w is the number of waypoints to generate and r is the clustering range.

There exist many mobility models but the reasons behind considering the SLAW and random mobility models among others are compound:

- It performs the best among others and random performs the worst [51], therefore, the best and worst cases of the mobility model are considered to justify the efficacy of this study.
- No other mobility model considers traces of human walk other than SLAW, which replicates the IoV in the smart city paradigm streets ahead.

Besides, this proposed enhancement is tested with the static network for two configurations: random and grid, as used in IoT network for both objective functions: existing OF-EC and proposed E-MOF. The work is further paralleled for random and SLAW mobile configurations as in the IoV network for both objective functions. Additional analysis has also been presented to apprehend the transformation of RPL used for IoT networks to RPL used for IoV networks in terms of network performance.

The considered and evaluated metrics to conduct this study are presented in Table 2 and Table 3 respectively.

Table 2. Considered Metrics

Metrics	Definition	Formula
Energy Consumption (EC)	It is the amount of total Energy Consumed by the nodes during the process.	$EC = ((T * 19.5mA\ + L * 21.5mA\ + CPU * 1.8mA\ + LPM * 0.0545mA) * 3V)/32768$ (4)
Expected Transmission Count (ETX)	It is defined as the total number of transmissions required to transmit	$ETX = \frac{1}{(Df * Dr)}$ (5)

	and acknowledge a packet over a wireless link.	
Hop Count (HC)	It is total number of hops made by each node for each source-destination pair.	--

Table 3. Evaluated Metrics

(3)

Metrics	Definition	Formula
Packet Delivery Ratio (PDR)	It is defined as the ratio of total number of successfully delivered packets to the total number of packets sent.	$PDR = \frac{Total\ number\ of\ received\ packets}{Total\ number\ of\ sent\ packets} * 100$ (6)
Control Traffic Overhead (CTO)	It is the total number of control messages exchanged during the simulation	$CTO = \sum_{x=1}^{m} DIO(x) + \sum_{x=1}^{n} DIO(x) + \sum_{x=1}^{o} DAO(x)$ (7)
Total Latency (TL)	It is the total delay observed in exchange of messages during the network lifetime.	$TL = \sum_{x=1}^{m}(Recieved\ Time(x) - Sent\ Time(x)$ (8)
Energy consumption (EC)	A network/setup is said to be energy efficient when the overall consumption of energy by the nodes is lesser than the threshold/standard results.	$EC = ((T * 19.5mA + L * 21.5mA + CPU * 1.8mA + LPM * 0.0545mA) * 3V)/32768$

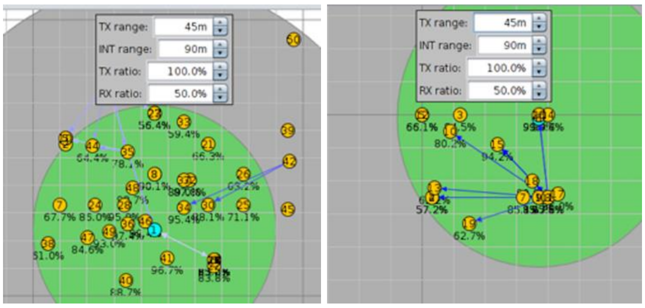
IV. Simulation Details and Results

A. Network Setup:

The proposed IoV network model utilizing E-MOF objective function is implemented using the Cooja simulator running on Contiki Operating System (version 2.7). Wireshark is used to analyze the network traffic and the BonnMotion tool [52] is used to generate SLAW mobility model positions for mobile nodes. These are open-source emulators and tools designed for recreating and testing various network scenarios. The values for all parameters are summarized in Table 4. An instance of an experimental test for random and SLAW configurations is shown in Fig. 6.

Table 4. Simulation Details

Parameters	Values
Network Simulator	Cooja/ Contiki OS 2.7
Network Analyzer	Wireshark
Mobility Generator	BonnMotion tool
Number Of Motes	10, 20, 30, 40, 50
Emulated Nodes	Sky mote
Propagation Model	UDGM (Unit Disk Graph Model) with distance loss
Static Environment (IoT)	Random and Grid
Mobile Environment (IoV)	Random and SLAW
Transmission (TX)	100%
Reception (RX)	50%
Interference (INT) Range	90 m
TX Range	45 m
Radio Traffic	6LoWPAN with pcap
Mote Startup Delay	65 s
Simulation Time	24 h



a) b)

Fig. 6. Experimental test-bed for a) random static model for 50 nodes using OF-EC and b) SLAW mobility model for 20 nodes using E-MOF

B. Results and Discussions:

To evaluate the performance of the proposed model, two different distributions (random and grid) are considered for the static environment, two distinctive mobility allocations (random and SLAW) are chosen for the dynamic environment and a mobile fuzzy-based objective function is considered. All the simulation figures illustrate RPL performances by considering the PDR, CTO, TL and EC metrics for 10 to 50 nodes. The network can also be scaled to a higher network size but due to computational limitations, it is out of the scope of this paper.

OF0 and MRHOF are the two standard objective functions used in RPL. It has been established in the literature [53] that MRHOF beats OF0. However, OF-EC [49] beats MRHOF, OF-FUZZY [50] and OF-ENTOT [54], all of these in terms of network performance. Thus, OF-EC proves to be superior among these objective functions [49]. Therefore, we choose OF-EC to compare our proposed objective function. Hence, a comparison has been made between the OF-EC and E-MOF for four evaluation metrics and two network configurations. The results are analyzed as follows:

1. Scalable Static (IoT) network

1) Packet Delivery Ratio (PDR):

Fig. 7. compares PDR for OF-EC and E-MOF for random and grid configurations to extrapolate the network reliability. It is known that the higher the PDR, the lesser the lost packets, superior is the network reliability. It can be observed that OF-EC gives the lower PDR when compared with E-MOF in both configurations as the network size increases. It is so because OF-EC uses metrics of ETX and HC, irrespective of other metrics influencing the network. Additionally, E-MOF performs better than OF-EC in random and grid configurations both. This can be justified by the use of combined/ composite metrics in E-MOF that considers link quality with a hop count and consumed energy also. However, the OF-EC achieves better results for grid configuration than random configuration by 8-9%. But, E-MOF for grid configuration performs marginally well by 0-1% than random configuration. The payoff of using E-MOF is that it is not much affected by the increase in network size, which signifies high reliability and better network performance for both low-density and high-density networks. It can therefore be concluded that E-MOF is superior to OF-EC for both configurations in IoT networks.

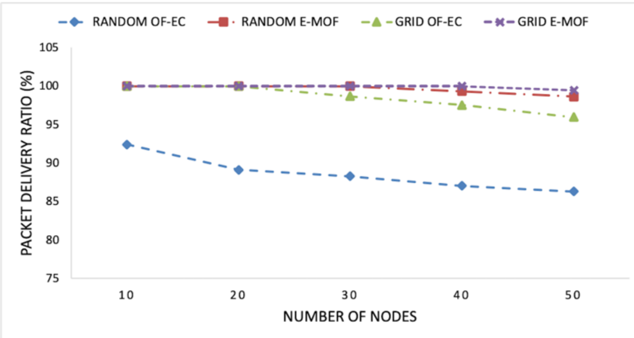


Fig. 7. Packet Delivery Ratio for two objective functions and two configurations

2) Control Traffic Overhead (CTO):

Internet Control Message Protocol version 6 (ICMPv6) handles the transmission of control messages. Fig. 8. shows the CTO for both objective functions and configurations. The ideal network will ensure lesser CTO and high network consistency. Though, the results illustrate that CTO increases with the increase in network size. Besides, OF-EC shows a significant rise in overhead with the increase in the number of nodes. It can be noted that OF-EC displays a higher overhead than E-MOF in both configurations. Also, OF-EC gives a higher overhead for random configuration than grid configuration by 762-5657 messages. While the E-MOF demonstrates lesser overhead for grid configuration than random by 700-2389 messages. The difference in overhead for E-MOF is relatively less than OF-EC overhead, which as a whole makes E-MOF excellent and suitable for IoT networks.

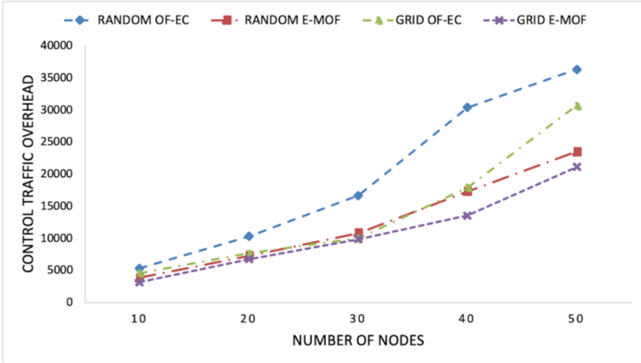


Fig. 8. Control Traffic Overhead for two objective functions and two configurations

3) Total Latency (TL):

Fig. 9. indicates a disparity of latency in terms of network scalability. Both configurations (random and grid) and both OFs (OF-EC and E-MOF) provide higher latency with the increase in several nodes. In the random configuration, the total latency of E-MOF is approximatively 1.127-3.388 secs higher than the total latency of the OF-EC objective function. In grid configuration, the total latency objective function EC is 1.066-1.659 secs higher than E-MOF. The high value of latency implies a crummy link quality. In the case of total latency of OF-EC and E-MOF, random configuration performs better than grid configuration by 4.120-7.389 secs and 1.928-2.342 secs respectively. However, the difference in values of E-MOF for both configurations is less than OF-EC values. Less volatility in values of latency shows improved link stability. Thus, E-MOF achieves superior performance than OF-EC and provides better link quality.

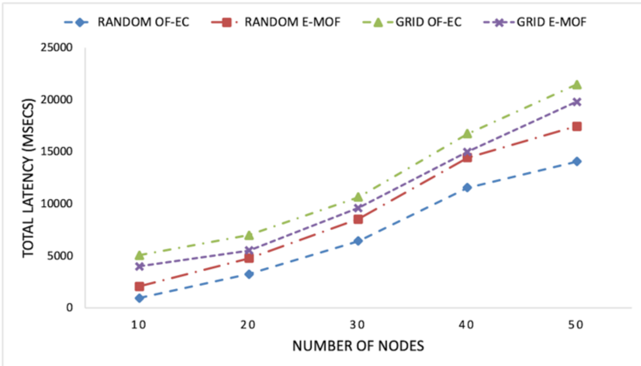


Fig. 9. Total Latency for two objective functions and two configurations

4) Energy Consumption (EC):

Fig. 10. displays energy consumed by nodes during network lifetime for two objective functions and two configurations. Ideally, a network should sustain its performance and reliability with low energy consumption by the nodes. This will ensure less energy depletion of nodes and longer battery life in the network. Nevertheless, it can be spotted from the results that more energy is consumed by nodes as the network size is increased. For random and grid configurations, OF-EC consumes less energy than E-MOF. Also, the difference between the consumed energy for OF-EC for random

configuration is 0.073-0.682 mW. While the difference in consumed energy for grid configuration using E-MOF is 0.832-1.173 mW. It is worth noting that the difference in values of consumed energy for OF-EC is intensifying with the increase in network size than the difference in values of consumed energy for E-MOF. Additionally, E-MOF gives better PDR and network reliability at the cost of consumed energy by nodes.

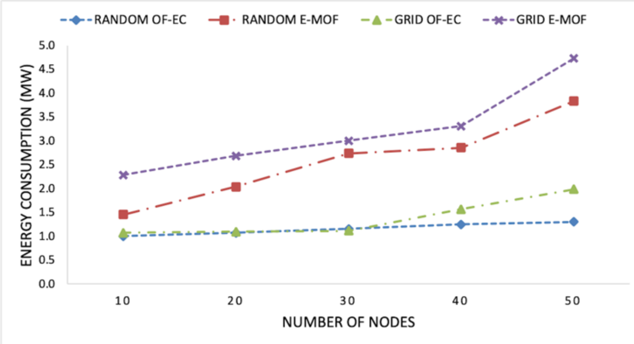


Fig. 10. Energy Consumption for two objective functions and two configurations

2. Scalable Dynamic (IoV) network

1) Packet Delivery Ratio (PDR):

It is well established now that the higher the PDR, the better the network trustworthiness and execution. Fig. 11. displays PDR with increasing network size for two OBJECTIVE FUNCTIONs (OF-EC and E-MOF) and two models (random and SLAW). It can be depicted that OF-EC is much lossy than E-MOF for both mobility models. E-MOF gives a higher PDR than OF-EC by 1-5% for the random mobility model. Whereas, E-MOF outperforms OF-EC for the SLAW mobility model by 3-8%. The difference between both objective functions for random and SLAW models are 5-7% and 7-13% respectively. However, the decrease in PDR with an increase in network size for OF-EC is significantly high. While E-MOF remains less disturbed with the increase in network density. Therefore, it can be inferred that an IoV network or V2I communication can use RPL with E-MOF objective function and follow the SLAW mobility model. Also, when the IoT network is equated to the IoV network, a minor difference of 3% PDR is observed which can be clearly explained by the mobility of nodes in the IoV network, since mobility induces frequent DODAG changes. This also justifies the use of the RPL protocol for the IoV network.

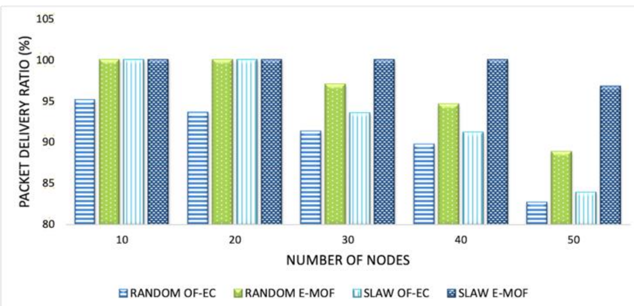


Fig. 11. Packet Delivery Ratio for two objective functions and two mobility models

2) Control Traffic Overhead (CTO):

Higher the CTO, the poorer the network robustness. Fig. 12. depicts CTO for two objective functions and two mobility models. The trend shows an exponential rise in CTO with the increase in the number of nodes. The bar graph clearly illustrates that E-MOF outdoes OF-EC for the SLAW model. Nevertheless, for the random model, E-MOF does better than OF-EC for 10 and 20 nodes but for a higher number of nodes, its performance degrades. However, the highest CTO is realized for OF-EC for the SLAW model. Also, it is noticeable that E-MOF shows a gradual rise in CTO values with an increase in network size as compared to OF-EC for both mobility models. The difference in the rise of CTO values using OF-EC for random is 64020 whereas, the difference in the rise of CTO values using E-MOF for the SLAW model is 60682, which is comparatively less than that of the random model and OF-EC objective function. Thus, it can be claimed that the proposed enhancement E-MOF using the SLAW model is better than OF-EC for IoV network implementation. When IoT network statistics are matched to IoV statistics, the IoV network generates a greater number of control messages than the IoT network, resulting in a higher CTO. This is explained by the high mobility of nodes which causes an increase in control routing operation. Although, it does not hamper the working of the RPL protocol for the IoV network and the protocol can be further advanced to increase network robustness.

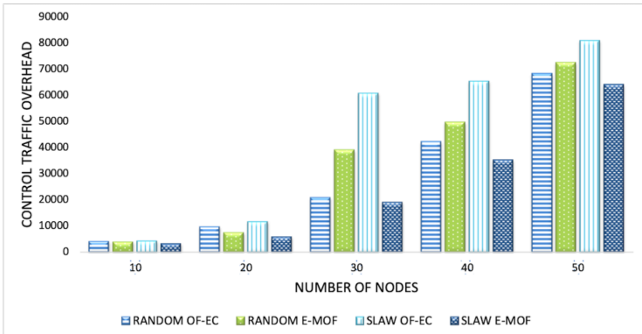


Fig. 12. Control Traffic Overhead for two objective functions and two mobility models

3) Total Latency (TL):

Fig. 13. denotes the difference in total latency concerning network scalability. It is distinct from the graph that OF-EC gives the worst performance and lousier network for both mobility models (random and SLAW). In the random model, the total latency of OF-EC is approximatively 3.103-9.199 secs higher than the total latency of the E-MOF objective function. In the SLAW model, the total latency of OF-EC is 0.87-4.848 secs higher than E-MOF. Consequently, E-MOF beats OF-EC for both models. Also, it is interesting to observe that the range difference in the TL values for the SLAW model is less than random model values, which marks the SLAW model mas ore competent for the IoV network. As the CTO increases for IoV network due to mobility of nodes, so does the TL, which is why RPL for IoT

network indicates less latency than RPL for IoV network. Although, the RPL protocol can be successfully used for V2I communication using the SLAW model and E-MOF with a slight reduction in total latency.

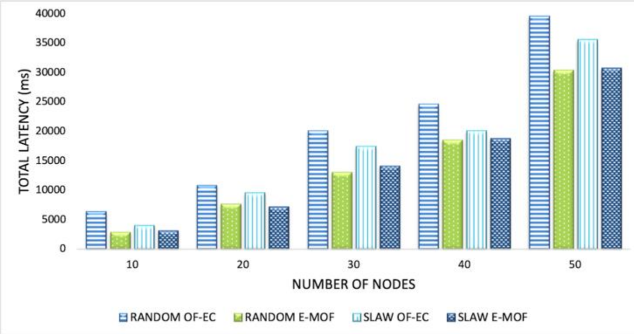


Fig. 13. Total Latency for two objective functions and two mobility models

4) Energy Consumption (EC):

The total energy consumption by nodes during the network lifetime for two OFs and two mobility models is depicted in Fig. 14. It is observed that E-MOF achieves high PDR at the cost of more EC. Preferably, a network ought to support its performance and dependability with low energy utilization by the nodes. This ensures less energy exhaustion of nodes and longer battery life. Though, it is not practically pragmatic. It is seen that EC increases with the increase in network size and high PDR. The graph shows that OF-EC consumes less energy than E-MOF in both models by 0.688-0.907mW and 0.441-2.389mW respectively. It can also be spotted that OF-EC performs better for the SLAW model than the random model by 0.239-0.291mW. Thus, it can be deduced that the SLAW model can be used to establish an IoV network using OF-EC. Nonetheless, RPL can be implemented for the IoV network with improvising E-MOF as it offers better PDR than OF-EC, which makes the network more reliable and efficient. Additionally, the IoT network is compared to the IoV network, and a difference of 0.419-0.907mW is calculated, which can be explained by frequent parent changes and high latency. Improvement in latency will improve EC of nodes and will mark E-MOF much better to use for IoV network using SLAW model and high PDR.

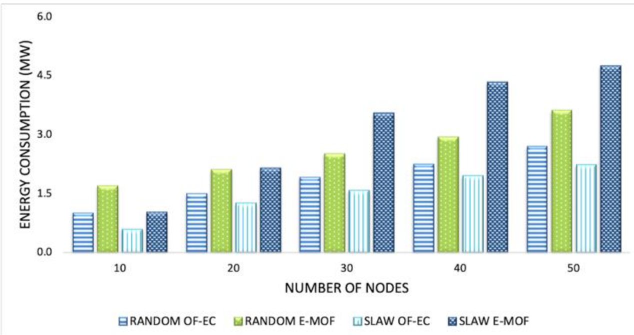


Fig. 14. Energy Consumption for two objective functions and two mobility models

V. Conclusion

This article gives an understanding of the RPL protocol which is fundamentally utilized for IoT networks only, as of now. The highlight is to feature the use of RPL protocol for the IoV network utilizing the proposed E-MOF objective function. The beginning of the article talks about the related studies. The problem proclamation is expressed where the need to utilize RPL for IoV network is underlined and since all RPL OBJECTIVE FUNCTION enhancements are just offered for IoT network, this paper proposes the utilization of RPL for IoV network by enhancing the recently recommended OF (OF-EC) referred to as E-MOF. Further, the working of E-MOF is clarified with simulation setup and details. The assessed performance metrics show E-MOF to be more competent than OF-EC. The effect of an increase in the number of nodes on the network performance is correspondingly studied. E-MOF offers better PDR, less CTO and comparable latency at the expense of high EC than OF-EC for both static and dynamic environments. The performance of E-MOF and OF-EC is examined for IoT scalable networks in two configurations: random and grid. Likewise, the two OBJECTIVE FUNCTIONs are tried for two distinct mobility models: random and SLAW for scalable IoV networks.

Results propose the use of grid configuration with E-MOF for static framework, while the SLAW mobility model with E-MOF is best for a dynamic network. This investigation additionally legitimizes the use of RPL for IoT as well as the IoV network. Although, the IoV network has to bear the expense of mobility in terms of network performance assessment when paralleled to the IoT network. But, this expense can be handily taken care of with RPL objective function enhancements for the IoV network and precludes the prerequisite to proposing a new protocol for IoV network communication altogether. Further, developing and improvising E-MOF for lesser energy consumption and lower latency for even superior network execution, robustness and reliability will be a part of future work. Determination of other metrics to test the network performance like nodes convergence, network lifetime, residual energy and so forth can likewise amount to further boosting E-MOF in future.

Declarations

1. Ethical Approval and Consent to participate: All authors have participated in this study and all ethics have been taken into consideration.
2. Human and Animal Ethics: Not applicable
3. Consent for publication: All authors have agreed to submit this version of the paper for publication.
4. Availability of supporting data: The data is included in the article. Still, excel datasheets can be provided on demand.
5. Competing interests: Authors declare no conflicting interests related to this work.
6. Funding: Not applicable
7. Authors' contributions: All authors have made significant contributions in conducting this study and writing the paper thereafter.

8. Acknowledgements: Authors would like to especially thank and acknowledge Dr Hanane Lamaazi for her guidance and assistance, without which this work would have been challenging.

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REFERENCES

[1] Lee, I., & Lee, K. (2015). The Internet of Things (IoT): Applications, investments, and challenges for enterprises. Business Horizons, 58(4), 431-440. https://doi.org/10.1016/j.bushor.2015.03.008

[2] Thangaramya, K., Kulothungan, K., Logambigai, R., Selvi, M., Ganapathy, S., & Kannan, A. (2019). Energy aware cluster and neuro-fuzzy based routing algorithm for wireless sensor networks in IoT. Computer Networks, 151, 211-223. https://doi.org/10.1016/j.comnet.2019.01.024

[3] Winter, T., Thubert, P., Brandt, A., Hui, J. W., Kelsey, R., Levis, P., Pister, K., Struik, R., Vasseur, J.P & Alexander, R. K. (2012). RPL: IPv6 Routing Protocol for Low-Power and Lossy Networks. *rfc*, *6550*, 1-157.

[4] Kim, H. S., Paek, J., Culler, D. E., & Bahk, S. (2020). PC-RPL: Joint control of routing topology and transmission power in real low-power and lossy networks. *ACM Transactions on Sensor Networks (TOSN)*, *16*(2), 1-32. https://doi.org/10.1145/3372026

[5] Lamaazi, H., & Benamar, N. (2020). A comprehensive survey on enhancements and limitations of the RPL protocol: A focus on the objective function. *Ad Hoc Networks*, *96*, 102001.

[6] Capone, S., Brama, R., Accettura, N., Striccoli, D., & Boggia, G. (2014). Energy efficient and reliable composite metric for RPL organized networks. In 2014 12th IEEE International Conference on Embedded and Ubiquitous Computing (pp. 178-184). https://doi.org/ 10.1109/EUC.2014.33

[7] Nassiri, M., Boujari, M., & Azhari, S. V. (2015). Energy-aware and load-balanced parent selection in RPL routing for wireless sensor networks. International Journal of Wireless and Mobile Computing, 9(3), 231-239. https://doi.org/10.1504/IJWMC.2015.073105

[8] Sebastian, A., & Sivagurunathan, S. (2018). Multi DODAGs in RPL for reliable smart city IoT. *Journal of Cyber Security and Mobility*, 69-86. https://doi.org/10.13052/2245-1439.716

[9] Lamaazi, H., El Ahmadi, A., Benamar, N., & Jara, A. J. (2019). OF-ECF: a new optimization of the objective function for parent selection in RPL. In *2019 international conference on wireless and mobile computing, networking and communications (WiMob)* (pp. 27-32). https://doi.org/10.1109/WiMOB.2019.8923273

[10] Hassani, A. E., Sahel, A., & Badri, A. (2021). IRH-OF: A New Objective Function for RPL Routing Protocol in IoT Applications. *Wireless Personal Communications*, 1-17. https://doi.org/10.1007/s11277-021-08230-8

[11] Luque-Vega, L. F., Michel-Torres, D. A., Lopez-Neri, E., Carlos-Mancilla, M. A., & González-Jiménez, L. E. (2020). Iot smart parking system based on the visual-aided smart vehicle presence sensor: SPIN-V. *Sensors*, *20*(5), 1476. https://doi.org/10.3390/s20051476

[12] Singh, P. K., Nandi, S. K., & Nandi, S. (2019). A tutorial survey on vehicular communication state of the art, and future research directions. Vehicular Communications, 18, 100164.

[13] Satyakrishna, J., & Sagar, R. K. (2018). Analysis of smart city transportation using IoT. In *2018 2nd International Conference on Inventive Systems and Control (ICISC)* (pp. 268-273). https://doi.org/ 10.1109/ICISC.2018.8399077

[14] Zhou, H., Xu, W., Chen, J., & Wang, W. (2020). Evolutionary V2X technologies toward the Internet of vehicles: Challenges and opportunities. *Proceedings of the IEEE*, *108*(2), 308-323. https://doi.org/ 10.1109/JPROC.2019.2961937

[15] Kezia, M., Anusuya, K.V. Mobility Models for Internet of Vehicles: A Survey. Wireless Pers Commun (2022). https://doi.org/10.1007/s11277-022-09637-7

[16] Kumar, A., & Hariharan, N. (2020, February). Enhanced mobility based content centric routing in rpl for low power lossy networks in internet of vehicles. In *2020 3rd International Conference on Intelligent Autonomous Systems (ICoIAS)* (pp. 88-92). IEEE.

[17] Garg, S., Mehrotra, D., Pandey, S., & Pandey, H. M. (2021, November). A Convergence Time Predictive Model using Machine Learning for LLN. In *2021 IEEE 8th Uttar Pradesh Section International Conference on Electrical, Electronics and Computer Engineering (UPCON)* (pp. 1-5). IEEE.

[18] Fabian, P., Rachedi, A., & Guéguen, C. (2020). Programmable objective function for data transportation in the Internet of Vehicles. *Transactions on emerging telecommunications technologies*, *31*(5), e3882.

[19] Royaee, Z., Mirvaziri, H., & Bardsiri, A. K. (2021). Designing a context-aware model for RPL load balancing of low power and lossy networks in the internet of things. *Journal of Ambient Intelligence and Humanized Computing*, *12*(2), 2449-2468.

[20] Idrees, A. K., & Witwit, A. J. (2021). Energy-efficient load-balanced RPL routing protocol for internet of things networks. *International Journal of Internet Technology and Secured Transactions*, *11*(3), 286-306.

[21] Mohammadsalehi, A., Safaei, B., Monazzah, A. M. H., Bauer, L., Henkel, J., & Ejlali, A. (2021). ARMOR: A Reliable and Mobility-aware RPL for Mobile Internet of Things Infrastructures. *IEEE Internet of Things Journal*.

[22] Manikannan, K., & Nagarajan, V. (2020). Optimized mobility management for RPL/6LoWPAN based IoT network architecture using the firefly algorithm. *Microprocessors and Microsystems*, *77*, 103193.

[23] Kniess, J., & de Figueiredo Marques, V. (2020). MARPL: A crosslayer approach for Internet of things based on neighbor variability for mobility support in RPL. *Transactions on Emerging Telecommunications Technologies*, *31*(12), e3931.

[24] Fotouhi, H., Moreira, D., Alves, M., & Yomsi, P. M. (2017). mRPL+: A mobility management framework in RPL/6LoWPAN. *Computer Communications*, *104*, 34-54.

[25] Theodorou, T., & Mamatas, L. (2020). SD-MIoT: A software-defined networking solution for mobile Internet of Things. *IEEE Internet of Things Journal*, *8*(6), 4604-4617.

[26] Syarif, A., Brahmia, MeA., Dollinger, JF., Abouaissa, A., Idoumghar, L. (2022). RPL-OC: Extension of RPL Protocol for LLN Networks Based on the Operator Calculus Approach. In: Yang, XS., Sherratt, S., Dey, N., Joshi, A. (eds) Proceedings of Sixth International Congress on Information and Communication Technology. Lecture Notes in Networks and Systems, vol 235. Springer, Singapore. https://doi.org/10.1007/978-981-16-2377-6_7

[27] A. K. Mishra, O. Singh, A. Kumar and D. Puthal, "Hybrid Mode of Operations for RPL in IoT: A Systematic Survey," in IEEE Transactions on Network and Service Management, doi: 10.1109/TNSM.2022.3159241.

[28] Gupta, N., Pughat, A., & Sharma, V. (2021). A critical analysis of RPL objective functions in internet of things paradigm. *Peer-to-Peer Networking and Applications*, 1-22.

[29] Kim, H. S., Kim, H., Paek, J., & Bahk, S. (2016). Load balancing under heavy traffic in RPL routing protocol for low power and lossy networks. *IEEE Transactions on Mobile Computing*, *16*(4), 964-979. https://doi.org/ 10.1109/TMC.2016.2585107

[30] Kharrufa, H., Al-Kashoash, H., & Kemp, A. H. (2018). A game theoretic optimization of RPL for mobile Internet of Things

applications. *IEEE Sensors Journal*, *18*(6), 2520-2530. https:doi.org/ 10.1109/JSEN.2018.2794762

[31] Arena, A., Perazzo, P., Vallati, C., Dini, G., & Anastasi, G. (2020). Evaluating and improving the scalability of RPL security in the Internet of Things. *Computer Communications*, *151*, 119-132. https://doi.org/10.1016/j.comcom.2019.12.062

[32] Zarzoor, A. R. (2021). Optimizing RPL performance based on the selection of best route between child and root node using E-MHOF method. *International Journal of Electrical & Computer Engineering (2088-8708)*, *11*(1). https://doi.org/10.11591/ijece.v11i1

[33] Kamgueu, P. O., Nataf, E., Ndié, T. D., & Festor, O. (2013). *Energy-based routing metric for RPL* (Doctoral dissertation, INRIA). https://hal.inria.fr/hal-00779519

[34] Toulabi, M., & Javadi, S. (2013). Energy-saving in Wireless Sensor Networks based on Sink Movement Control using fuzzy logic. *Journal of Wireless Sensor Networks*. 1-3.

[35] Gaddour, O., Koubâa, A., & Abid, M. (2015). Quality-of-service aware routing for static and mobile IPv6-based low-power and lossy sensor networks using RPL. *Ad Hoc Networks*, *33*, 233-256.

[36] Lamaazi, H., & Benamar, N. (2017). RPL enhancement using a new objective function based on combined metrics. In *2017 13th international wireless communications and mobile computing conference (IWCMC)* (pp. 1459-1464). https://doi.org/ 10.1109/IWCMC.2017.7986499

[37] Solapure, S. S., & Kenchannavar, H. H. (2020). Design and analysis of RPL objective functions using variant routing metrics for IoT applications. *Wireless Networks*, *26*, 4637-4656. https://doi.org/10.1007/s11276-020-02348-6

[38] Gopika, D., & Rukmani, P. (2021, May). FSS: Fuzzy Supervised Learning for Optimal Path Selection in RPL. In *Journal of Physics: Conference Series* (Vol. 1911, No. 1, p. 012016). IOP Publishing.

[39] Bang, A. O., & Rao, U. P. (2022). EMBOF-RPL: Improved RPL for early detection and isolation of rank attack in RPL-based internet of things. Peer-to-Peer Networking and Applications, 15(1), 642-665.

[40] Fazli, F., & Mansubbassiri, M. (2022). V-RPL: An effective routing algorithm for low power and lossy networks using multi-criteria decision-making techniques. *Ad Hoc Networks*, *132*, 102868.

[41] Fotouhi, H., Moreira, D., & Alves, M. (2015). mRPL: Boosting mobility in the Internet of Things. *Ad Hoc Networks*, *26*, 17-35.

[42] Bouaziz, M., Rachedi, A., Belghith, A., Berbineau, M., & Al-Ahmadi, S. (2019). EMA-RPL: Energy and mobility aware routing for the Internet of Mobile Things. *Future Generation Computer Systems*, *97*, 247-258.

[43] Gaddour, O., Koubäa, A., Rangarajan, R., Cheikhrouhou, O., Tovar, E., & Abid, M. (2014, June). Co-RPL: RPL routing for mobile low power wireless sensor networks using Corona mechanism. In *Proceedings of the 9th IEEE international symposium on industrial embedded systems (SIES 2014)* (pp. 200-209). IEEE.

[44] Ghaleb, B., Al-Dubai, A., & Ekonomou, E. (2015, October). E-trickle: Enhanced trickle algorithm for low-power and lossy networks. In *2015 IEEE International Conference on Computer and Information Technology; Ubiquitous Computing and Communications; Dependable, Autonomic and Secure Computing; Pervasive Intelligence and Computing* (pp. 1123-1129). IEEE.

[45] Kumar, J. S., & Suresh, D. (2022). Design and implementation of a mobility support adaptive trickle algorithm for RPL in vehicular IoT networks. *International Journal of Ad Hoc and Ubiquitous Computing*, *40*(1-3), 38-49.

[46] Verma, A., & Ranga, V. (2020). Security of RPL based 6LoWPAN Networks in the Internet of Things: A Review. *IEEE Sensors Journal*, *20*(11), 5666-5690. https://doi.org/ 10.1109/JSEN.2020.2973677

[47] Pancaroglu, D., & Sen, S. (2021). Load balancing for RPL-based Internet of Things: A review. *Ad Hoc Networks*, 102491. https://doi.org/10.1016/j.adhoc.2021.102491

[48] Garg, S., Mehrotra, D., Pandey, H. M., & Pandey, S. (2021). Accessible review of internet of vehicle models for intelligent transportation and research gaps for potential future directions. *Peer-to-Peer Networking and Applications*, 1-28. https://doi.org/10.1007/s12083-020-01054-6

[49] Lamaazi, H., & Benamar, N. (2018). OF-EC: A novel energy consumption aware objective function for RPL based on fuzzy logic. *Journal of Network and Computer Applications*, *117*, 42-58. https://doi.org/10.1016/j.jnca.2018.05.015

[50] Kamgueu, P. O., Nataf, E., & Djotio, T. N. (2015). On design and deployment of fuzzy-based metric for routing in low-power and lossy networks. In *2015 IEEE 40th Local Computer Networks Conference Workshops (LCN Workshops)* (pp. 789-795). https://doi.org/ 10.1109/LCNW.2015.7365929.

[51] Garg, S., Mehrotra, D., Pandey, S., & Pandey, H. M. (2021). Network efficient topology for low power and lossy networks in smart corridor design using RPL. *International Journal of Pervasive Computing and Communications*. https://doi.org/10.1108/IJPCC-08-2020-0118

[52] Aschenbruck, N., Ernst, R., Gerhards-Padilla, E., & Schwamborn, M. (2010, March). Bonnmotion: a mobility scenario generation and analysis tool. In *Proceedings of the 3rd international ICST conference on simulation tools and techniques* (pp. 1-10). https://doi.org/10.4108/ICST.SIMUTOOLS2010.8684

[53] Pradeska, N., Najib, W., & Kusumawardani, S. S. (2016, October). Performance analysis of objective function MRHOF and OF0 in routing protocol RPL IPV6 over low power wireless personal area networks (6LoWPAN). In *2016 8th international conference on information technology and electrical engineering (ICITEE)* (pp. 1-6). IEEE.

[54] Demicheli, F. (2011). Design, implementation and evaluation of an energy-efficient RPL routing metric.

APPENDIX

List of Abbreviations	**Description**
AMI	Advanced Metering Infrastructure
CTO	Control Traffic Overhead
DIO	DODAG Information Object
DAO	Destination Advertisement Object
DIS	DODAG Information Solicitation
DAO-Ack	DAO-Acknowledgment
DODAG	Destination Oriented Directed Acyclic Graph
ETX	Expected Transmission Count
ETC	Electronic Toll Collection
HC	Hop Count
EC	Energy Consumption
ICMPv6	Internet Control Message Protocol version 6
IPv6	Internet Protocol version 6
IETF	Internet Engineering Task Force
IoT	Internet of Things
IoV	Internet of Vehicles
6LoWPAN	IPv6 Low power Wireless Personal Area Networks
LLNs	Low Power and Lossy Networks
PDR	Packet Delivery Ratio
QoS	Quality of Service
ROLL	Routing Over Low power and Lossy networks
RPL	Routing Protocol for Low Power and Lossy Networks
RSSI	Received Signal Strength Indicator
RSU	Road Side Unit
RX	Reception
SLAW	Self-similar Least Action Walk
TL	Total Latency
TMS	Traffic Monitoring System
TX	Transmission