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# DDSLA-RPL: Dynamic Decision System Based on Learning Automata in the RPL Protocol for Achieving QoS

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**ABSTRACT** The internet of things is a worldwide technological development in communications. Low Power and Lossy Networks (LLN) are a fundamental part of the internet of things with numerous monitoring and controlling applications. This network has many challenges as well, due to limited hardware and communication resources, which causes problems in applications such as routing, connections, data transfer, and aggregation between nodes. The IETF group has provided a routing model for LLN networks, which expands IPv6 protocol based on Routing Protocol (RPL). The pro-posed decision system DDSLA-RPL creates a list of limited k member optimal parents based on qualitatively effective parameters such as hop, link quality, SNR rate, and ETX energy consumption, by informing child nodes of their connection link to available parents. In the routing section, a decision system approach based on learning automata has been proposed to dynamically determine and update the weight of influential parameters in routing. The effective parameters in the routing phase of DDSLA-RPL include battery depletion index, connection delay, and node queuing and throughput. The results of the simulation show that the proposed method outperforms other methods by about 30, 17, 20, 18, and 24 percent in mean longevity and energy efficiency, graph sustainability, operational power and latency, packet delivery rate test, and finally number of control messages test, respectively.

**INDEX TERMS** Internet of Things, routing protocol, routing, quality of service, dynamic decision system, learning automata.

## I. INTRODUCTION

With the major developments of technology and the increasing popularity of digital tools and infrastructure, the communication needs of societies have undergone significant alteration. These changes have been effective in quality of life, jobs, and aspects of urban life. Therefore, the technology required to improve these practical areas involves structured communication. The internet of things has been recognized as a suitable scenario to influence human lives, which can merge modern technology with future life. The internet of things has expanded the definition of the world web from merely a homogenous network of computers connected to the internet, to a network of heterogeneous gadgets and appliances like home appliances, mobile electronic devices, and wireless sensor networks [1], [2]. Today, the internet of things is a world issue, and because of its increasing applications, it has created a large amount of data. These data must be first transferred to target servers to be processed. This transfer of data from A to B must be carried out correctly and without error and latency which has revolutionized routing in this network [3]. The limitations and challenges of routing in the sensor network, as the

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most important part of the internet of things, distinguishes it from other distributed systems [4]. These limitations affect the design of wireless sensor networks including protocols and algorithms different from other categories of the internet of things. The research area of the present study focuses on the structure of graph construction and routing in the internet of things [5]; therefore, some of the most important limitations in sensor routing are considered which include, traffic patterns, energy efficiency, scalability, motion, two-way links, and the rate of radio transmission. In recent years, many routing protocols have been proposed in the field of sensor networks and LLN, each with a specific purpose in the network. After the idea of the internet of things and connecting mobile digital devices through the internet, a need for multi-hop connections arose and researchers are seeking to design and implement a standard routing protocol based on 6LowPAN [6] to alleviate the current and future needs of the internet of things. In the present study, a quality-aware service approach is pro-posed based on a multiple-criteria decision system called DDSLA-RPL. The manuscript is categorized as follows; in part two, routing protocols in this type of network are reviewed and in part three, the proposed method is introduced. In part four, the results pertaining to the simulations and practical tests for use in the internet of things based on proper metrics are presented. Finally, part five concludes the research.

## II. REVIEW OF PAST RESEARCH

In the world of distributed communication and heterogeneous networks, the network nodes do not always possess high resources and computing ability and often face limitations such as hardware resources, the short-range of radio signals, low transfer rate, and data production. Simply put, LowPAN is a simple and inexpensive network connection, which allows nodes with limited energy sources to connect to each other. The nodes in the LowPAN network use the IEEE 802.15.4 standard to connect to each other. With the requirements of IPv6 based networks [7], the LLN networks [8] and consequently, the internet of things has undergone a structural change, which led to a wave of new research in the field of network routing protocols [9]. In this section, the most well-known basic routing protocols for the internet of things are introduced and their standard abilities in this platform are assessed.

### A. RPL PROTOCOL

Based on the specifications mentioned for 6LowPAN networks and generally, for LowPAN and LLN network, routing is of great importance in this type of network. Previously, protocols had been designed for LLN networks, none of which presented a comprehensive and standard solution for these types of networks. As a result, a task force ROLL in the IETF organization introduced a routing protocol named RPL, which is the main candidate for a standard routing protocol in LLN networks. This taskforce introduced other RFCs in

**TABLE 1. Units for magnetic properties.**

| Symbols and Variables | Definition |
|---|---|
| $OF$ | Objective Function |
| $MHROF$ | Minimum Rank with Hysteresis OF |
| $ETX$ | Expected Transmission Count |
| $HC$ | Hop Count |
| $BDI$ | Battery Discharge Index |
| $NRE$ | Node Residual Energy |
| $RSSI$ | Received Signal Strength Indicator |
| $LQL$ | Link Quality Level |
| $SNR$ | Signal-to-Noise Ratio |
| $PLR$ | Packet Loss Rate |
| $MCDM$ | Multi-Criteria Decision Making |
| $LCI$ | Life cycle index |
| $PDR$ | Packet Delivery Ratio |
| $\varphi\Delta t$ | Queue Input Rate |
| $\mu\Delta t$ | Queue Output Rate |
| $CER$ | Composite Efficient Routing |
| $W\text{-}SPH$ | Wireless Shortest Path Heuristic |
| $PMFR$ | Proactive Multicast Forwarding RPL |
| $\delta$ | Standard Deviation |
| $\mathcal{E}$ | Matrix Element |
| $w$ | The Weight of Parameters |
| $LSM$ | Least Square Method |
| $AHP$ | Analytic Hierarchy Process |
| $\Psi$ | Decision system result |
| $Root$ | The root node of the graph (Sink) |
| $G$ | Graph |
| $V$ | V is a set of vertices |
| $E$ | E is a set of edges |
| $S$ | Set of nodes |
| $\Omega$ | Graph degree constant |
| $PL$ | Parent List |
| $CORR$ | Hardware correlation |
| $E_{Alive}$ | The Energy consumption for radio |
| $E_{CCA}$ | The Energy consumption for CCA |
| $E_{DIO,DAO,DIS}$ | The Energy of control messages |
| $Df$ | Delivery forward |
| $dr$ | Delivery reverse |
| $PC$ | Power consumption |
| $L$ | Length of Packet |
| $\rho$ | Link Exchange Rate |
| $RER$ | Residual Energy Ratio |
| $QSI$ | Queue State Index |
| $LDI$ | Link Delay Index |
| $TI$ | Throughput Index |
| $\tau$ | Time interval |
| $\delta$ | standard deviation |
| $\alpha$ | Rewards in Automata |
| $\beta$ | Penalties in Automata |
| $c$ | A set of penalty probabilities |
| $d$ | A set of rewards probabilities |
| $P_{w_i}$ | Probability of weight changes |
| $\vartheta$ | Number of parameters |
| $\gamma$ | Threshold in Automata |
| $D_{jk}$ | Euclidian distance between node j and k |
| $ACK$ | Acknowledge message |
| $LT$ | Lifetime |
| $w_i$ | Weight of rule i |
| $U_i$ | The total cost of parameters |
| § | The boundary of answer |
| $K$ | A Constant parameter in trickle timer |
| $\lambda$ | Exponential distribution |
| $ALTN$ | Average Life-Time Network |
| $m$ | Number of alive nodes |
| $t_i$ | Dead time of node i |
| $PDR$ | Packet Delivery Ratio |
| $M$ | Number of alive nodes |
| $N$ | Total number of network nodes |
| $T$ | Predefined network lifetime |
| $JFI$ | Jain's fairness index |
| $l$ | The loss rate of Energy |

other applications of LLN networks; namely, RFC 5548, RFC 5826, RFC 5673, and RFC 5867 [10].

The RPL is a distance-vector protocol, which operates, based on source routing. This protocol transfer's data, based on several methods, point-to-point connection LLN (between devices or nodes), point-to-multipoint LLN (from one central control point to a collection of nodes), and multipoint-to-point (from the collection of LLN nodes to one central control point). The RPL protocol works based on a graph called DODAG that is the basis for all activities in the routing protocol. In the following, this graph and its interaction with the new versions of RPL are introduced and discussed.

### B. OBJECTIVE FUNCTION IN RPL

The practical RPL protocol has been designed for diverse environments that support important properties in the network's objective function; such as preventing and discovering loops in the DODAG graph, repairing routes or out of service nodes, and supporting various types of metrics and regulations. The RPL routing protocol is a protocol that can alleviate the network's various requirements. Considering the various practical applications of these types of networks and having different regulations, therefore, it cannot be expected that a fixed combination of metrics will be beneficial in all applications. Therefore, the RPL protocol is flexible with different types of networks. The main purpose behind the objective function in the RPL protocol is to make this protocol more flexible in different areas and applications. An interesting fact in the design of the RPL protocol is that it is a combination of two topologies, mesh and hierarchical. This design will make the RPL protocol flexible in routing and topology management. The RPL forces the nodes to organize in a hierarchy and create a parent-child relation. On the other hand, in times of need, RPL allows the nodes to use sibling nodes instead of parent nodes to send packets. In fact, each node has a list of candidate parent and sibling nodes within itself; and the nodes in this list are used whenever the current parent node lacks the ability to send packets. Based on the definition provided in the RFC documentary about the RPL proto-col, the objective function determines how the network nodes choose their route. In other words, the objective function determines how the nodes turn the metrics and principles into ranks to be able to choose a suitable parent [11].

Based on this definition, OF has the main role in finding and improving the routes between nodes and it is the OF that decides which nodes can join the route according to available metrics and principles. In an RPL network, a node can have several parents. Up until now, the IETF ROLL has published two standard objective functions with RFC for the RPL protocol. One is called Objective Function Zero or OF0 for short and the other is the Minimum Rank with Hysteresis Objective Function or MRHOF. The OF0 uses the best parent metric to choose ''the least number of jumps'' and the MRHOF uses the ETX metric to find the best routes. When the network uses MRHOF as the objective function, it is obvious that the route with the lowest ETX is chosen as the optimum route towards the root. However, one objective function cannot be used for various applications and situations; and RPL's strong point is that it can be optimized for any application using OF. In fact, the OF must be designed according to the type of application it is required to perform. This is an issue that researchers have begun to redefine in their current studies.

### C. NETWORK MANAGEMENT METRICS

The available metrics for routing are so important that RFC has been written for them (RFC 6551) and in that documentary, their properties have been explained extensively. We aim to introduce some of the most important routing metrics and provide a short description for each one. Some of the important routing metrics can be categorized as follows:

#### 1) NODE METRICS

- **Node Energy:** the energy of a node or its battery is considered an important factor in many LLN networks. For this reason, in many networks, longer routes are chosen to reach the root in order to increase node and network longevity. The transmitter has the highest battery consumption in the nodes; as a result, either work has been done to regulate the transmitter strength or the nodes are distanced as much as possible so that they cover a larger area. One of the metrics related to energy is the BDI metric which has been introduced based on the RER metric in [12] and [13].
- **The number of hops:** which is shown as HC in many kinds of works of literature, is the number of required hops for the packet to reach its destination. In many studies, this metric has been used as a basis for creating the DODAG graph or routing. The base metric in the standard objective function OF0 is also the number of hops.
- **Delay:** as you know, four types of delay are present in network concepts. These are release delay, processing delay in the node, queuing delay, and sending delay. Some of these delays are inherent properties of the network and cannot be improved using objective functions. Others on the other hand, like queuing delay, can be improved through some measures.

#### 2) LINK METRICS

- **ETX:** the expected transmission rate of the link is an important index of network reliability. Based on the ETX definition, it is the number of times required to transmit a packet in order to reach its destination correctly. In other words, the number of transmissions a node must perform to deliver the packet correctly. Another definition of ETX is available and it is the total number of transmissions divided by the number of successful transmissions. The range of ETX can be from one to infinity; if ETX equals 1 it means link quality is extremely high. As ETX moves towards infinity, link quality declines.
- **RSSI:** the physical layer provides the possibility of determining the network connection properties such as

**TABLE 2. Frequently used metrics in research from 2014 to 2020.**

| Metrics | Percentage used in Research |
|---|---|
| Energy Consumption | 0.28 |
| ETX | 0.1 |
| Packet Delivery Ratio | 0.15 |
| Hop Count | 0.09 |
| Latency | 0.04 |
| Convergence time | 0.04 |
| Throughput | 0.09 |
| Receive Packet | 0.05 |
| Loss Packet | 0.04 |
| PLR | 0.06 |
| Other metrics* | 0.06 |

* Other metrics are presented in Table III.

**TABLE 3. Other metrics in research.**

| Metrics | Percentage used in Research |
|---|---|
| Churn | 0.16 |
| Duty Cycle | 0.16 |
| Duplicate Packet | 0.15 |
| Malicious Nodes | 0.16 |
| Probability of forwarding | 0.11 |
| Number of Transmission | 0.14 |
| Frame Count | 0.12 |

signal, frequency, voltage, etc. The best way to estimate the radio link is the signal strength index received from the RSSI index, which is a function of the nodes transmission power and is conversely related to the distance factor.

- **SNR:** this metric is the ratio of signal to noise in the connection link between two nodes. Signal refers to the quality of the connection and noise refers to the connection failure rate. In other words, the signal is the expected status and noise is the amount of disturbance or fault in the signal. The low transmission rate and limited resources in the LLN networks lead to a lower signal to noise ratio and consequently results in lower data transmission quality. Similar to node metrics, other metrics can be designed from a combination of the aforementioned metrics.
- **LQL:** the link quality index LQL estimates and presents the reliability of the link using a range of 0 to 7. This metric directly affects the packet delivery rate (PDR).
- **Throughput:** this index addresses the mean number of successful connections in a link and is one of the key factors in identifying, controlling, and managing network congestion.

## III. THE PROPOSED DDSLA-RPL METHOD

The challenges discussed for providing quality services in the internet of things routing are mostly a result of lack of balance, fairness, intelligent routing and topology control. Based on the alignment pattern for the RPL protocol, this protocol consists of two main phases, which include the formation of the network tree and the steady state phase. The universality of these two phases typically causes researchers to look at it from a one-dimensional perspective, for example studying merely on the first or second phase. Therefore, we have focused our study on both phases of the RPL protocol since correct decisions in these two phases are correlative. In other words, a precautionary approach is much more beneficial and cheaper than confrontational approaches or periodical decisions in a network based on RPL. Based on previous studies, using one or more link or node metrics, or even avariciously using them together, is not necessarily beneficial. As a consequence of one-way traffic towards the root, the closer we get to the root the quality of services from the parent nodes close to the root becomes critical; because the funnel effect of traffic has been drawn to them, and in the circumstance that received data is not transferred in due time, the queue buffer will overflow and eventually lead to packet loss. This effect of congestion was proven in our previous studies [5] and [42]; however, the proposed model in the present study named DDSLA-RPL consists of two main phases. For this purpose, we have proposed a multi-criteria and multi-object system to make dynamic decisions based on effective metrics in service quality within two phases of graph formation and routing. In section 3-1, the different stages of the decision system are described.

### A. STAGES OF THE DECISION SYSTEM

Every decision is made at least for one specific object which achieving it depends on other influential variables within a decision making model. The object of the decision is called the dependant variable and other influential variables are independent variables. This decision system includes six main steps:

- *Step 1:* In solving multi-indicator problems, the exact definition of object/objects is an important issue. In the present study, our objects, if it be service quality or reducing energy consumption and increasing network lifetime, are all considered objectives; however, because at the onset of the network energy criteria is not the first priority thus the proposed decision system follows the other network service quality criteria which in the duration of the network activity have different priorities based on node status and connection links.
- *Step 2:* After accurately describing the problem, factors, with obtainable data, that affect the object of the problem must be determined. In section 3-2 of the present study, the relative network management metrics and their measurement methods have been presented. Considering that some metrics are qualitative and some are quantitative, they will have different places, roles, coefficients, and priorities in the decision system computations. Separating positive and negative indicators is performed in this step.
- *Step3:* Options either are known and only require decision-making or with researching the problem

**TABLE 4. Advantages and disadvantages of recent methods on the RPL protocol.**

| Year/RFC | Process | Advantages | Disadvantages |
|---|---|---|---|
| 2014 ORPL [14] | An opportunistic model on the RPL protocol uses hops as the graph creating metric. In this method, several available parent nodes do routing. | This network aims to increase longevity in relay nodes and it succeeds to a certain degree. Competition between parents' nodes has reduced computing overload. | The end-to-end delay index for the packet has not been addressed. In addition, there is no test to estimate the status and queue overflow of the nodes. |
| 2015 QRPL [15] | In this method, two criteria of energy and delay are the inputs to a system based on an ant colony. The selection criteria are the level of pheromones in the route. Route energy rate and delay are cumulatively calculated from the root to the parent. | The introduced method can only satisfy energy and delay as criteria for the quality of network services. | Considering the reconnecting of sensor nodes to the network and the manner of determining new parents, there are no discussions. In addition, the coordination among incoming traffic to the parent is not evaluated. |
| 2015 BD-RPL [16] | This method focuses on limiting the graph's rank. By allocating a fixed number like k, the graph is constructed such that the highest rank of each node is k. In other words, each node can have k children. | In this method, the number of control messages is reduced; therefore sustaining excess traffic load by the network will be prevented. | In the design of the graph, attention has only been paid to the rank of the graph and other important metrics such as ETX and route quality have been neglected. Neglecting the link quality can inflict major consequences on the network. In addition, no attention is paid to the energy level of the node, which is supposed to be the parent node. |
| 2015 CRPL [17] | This method has been carried out on the ORPL algorithm. The set of parents available to the node are considered as a cluster and based on the competition between parents, attraction and transmission takes place. In addition, the ETX metric is the computing criteria. | Limiting node transmissions through clustering parent nodes has greatly prevented the occurrence of hidden terminals. | Similar to ORPL, the delay metric has not been considered in computations. |
| | In this paper, it has been introduced as a flexible method for networks with several DODAG. Considering hop, ETX, and PDR delivery rate metrics have made the network graph suitable for various applications. | There is the possibility of running the protocol in environments with a high variety of data and where node sensors detect several parameters. | The lack of aggregating data in this method is evident. Network data diversity and the priority of network packets make any queue timing impossible. In addition, a lot of energy is consumed for cooperation between different DODAGs, which reduces algorithm efficiency. |
| 2016 HECRPL [19] | The authors of CRPL have presented a newer study called HECRPL, which has optimized the clustering and the convergence between parents in each cluster. The delay and transmission energy metrics based on parents play a major role in this method's computations. | Considering the delay metric, which was CRPL's weak point, is this new method a strong suit. The main goal of this method has been to increase network lifetime. | CPS is a time-consuming mechanism that increases the convergence time of the network graph. Also in this method, there is no research on the repair and recreation of the network graph, which seems to create a challenge for the network. |
| 2016 LB-OF [20] | In this method, to control the number of children in each node, the DIO messages sent from child to parent are counted. In typical methods, this message is thrown away. | This method is useful and practical for nodes that are considered choke points and have low battery consumption. | This method only considers the network's battery consumption aspect and neglects link quality metrics. Similar to other methods, it also neglects overflow and congestion in the parent node. |
| 2016 CA-RPL [21] | In this method, the author uses a mixed metric called LATENCY-ROOT, which combines ETX, rank, and the number of successfully received packets. | This method proves useful in reducing the rate of lost packets and latency. | Queue status and load balancing in the network have not been assessed. |
| 2016 QU-RPL[22] | In this method, a load balance mechanism sensitive to node congestion is introduced. Each node decides on losing its children based on congestion criteria. In a sense, this decision is fair and with the intention of preventing congestion transfer. | This method has had great success in reducing lost packets in node queue and in increasing packet delivery rate in the network. | Practically, this method has provided no solution to decrease energy consumption and delay rate. |
| 2017 IRPL[23] | This method uses two link and node metrics simultaneously. The lifetime cycle index (LCI) is computed for each parent node and child nodes benefit from the multi-route option for data transmission in case of congestion. | Using the multi-route mechanism to create load balance and latency the death of the first node in the network are some of the benefits of this method. | There are no arguments considering calculating the delay, queue status and how the best option for parent (alternative parent) is chosen. It seems, the parent choosing criteria is only LCI that is carried out greedily. On the other hand, the effect of imbalance in node children has not been assessed. |
| 2017 Multi-GW [24] | The child node chooses a route towards the root with the least number of jumps. If the number of such routes is more than one, a route is chosen using the tiebreaker metric provided by the parents. | Using a tiebreaker metric in the network can be beneficial in different scenarios. | In this method, tiebreaker metrics are not a combination of metrics and only one aspect of the network is considered. In addition, none of the tiebreaker metrics includes the residual energy of the node. |
| 2017 [12] | In this method, the two metrics of network traffic and battery depletion rate are chosen as the parent selection criteria. A node with less traffic and lower battery depletion will have a better rank. | Considering the metrics effective in increasing network lifespan has led to a balance in energy consumption rate in parent nodes. | In this method, there is no consideration of possible collision, congestion and queue overflow in the parent node. This weak point, which is a consequence of the funnel effect in the network, will create many negative outcomes such as frequent node transmissions and excess load. |

**TABLE 4.** ***(Continued.)*** **Advantages and disadvantages of recent methods on the RPL protocol.**

| | | | |
|---|---|---|---|
| 2017 [25] | Each node first creates a collection of its neighbours and then orders them based on the ETX metric and the three nodes with the best status are separated. Then these three are organized based on the RSSI metric. Thus, the metric with the best status for ETX and RSSI is chosen and the required power for data transmission is estimated. | The combination of several link metrics has led to increased network flexibility and in a way prevents multiple link failures in the network. | This method imposes a high computing and control overload on the nodes, which leads to increased energy consumption in parent nodes. |
| 2017 ERAOF [26] | In this paper, the combination of ETX and consumed energy metrics are sent in conjunction with the parent. In the end, a link quality metric is created for every route and any route with the highest link quality is selected. | A combination of two or more metrics means that the network is not assessed one dimensionally and other aspects are considered. | The computational overload of this method is a bit high which can lead to early battery depletion. |
| 2017 LB-RPL [27] | In this method, the packet ready for transmission in the child node, is distributed among n parents. Also, if the parent is facing congestion, it latency's its packet transmission therefore the child removes the congested parent node from its list. | This method improves packet delivery rate and passing. | The mentioned method is not optimized in energy consumption. In addition, similar to other methods, it neglects the overflow and congestion in the parent node. |
| 2017 [28] | The author has assessed and analysed two common network objective functions, OF0 and MRHOF and compared them in different aspects such as ETX, number of hops, number of lost packets, energy and traffic overload. | In most tests, the OF0 function performed better than the MRHOF. | Latency and queue status are left out of this study. |
| 2017 [29] | This method is an improvement on the objective function known as MRHOF; and instead of using only one ETX metric, it utilizes the energy metric as well. | This modification in the objective function improves PDR without increasing energy consumption within nodes. | In this method, congestion and queue overflow in the parent node have been neglected. This weakness will lead to many problems such as frequent node transmissions and bearing excessive load in the network. |
| 2018 SIGMA-ETX [30] | In this method, the two metrics ETX and number of hops have been combined and a metric called SIGMA-ETX created. This study has compared and chosen the route's mean ETX rate to transfer the packet. | This method has optimally utilized aspects such as packet delivery rate and latency. | Considering energy consumption, It performs less efficiently as compared to OF0 and MRHOF objective functions. In addition, congestion and queue overflow in the parent node have been neglected in this method. This weakness will lead to many problems such as frequent node transmissions and bearing excessive load in the network. |
| 2018 OF-EC [31] | In this method, the author has combined ETX and node metrics (energy consumption and hops) using fuzzy logic and ultimately obtained the best choice for packet transmission. | Thanks to the metric, the network will not be viewed in one dimension and other aspects will be considered. | The parent node has not been assessed in different network traffic conditions. Thus, this network has a high number of retransmissions without any explanations. |
| 2019 E-RPL [32] | A routing pattern based on ant colony with the aim of increasing energy efficiency in RPL networks. In this method, the efficiency of choosing parents depends on pheromones and their evaporation factor. Quantitative and qualitative criteria have been considered in this algorithm to lower network trickle timer reset. | In this method, a combination of ETX and PDR mechanisms have been used as throughput indicator and remaining energy and number of node children have been used as energy efficiency indicator. | This method has not determined an indicator for queue status and collision probability. Also based on the topic of the study it was expected that the authors address the number of trickle timer resets and its probability based on the network's instabilities. |
| 2019 COLBA [33], [34] | The node metric in this method is a "traffic intensity" type. If the metric amount is higher than 1 and also $(\lambda\Delta t - \mu\Delta t)$ is more than the number of empty spaces in the queue, the parent sends a beacon to its child nodes and asks them to decrease their packet transmission 50%, then 75% and finally stop transmission. | To remove congestion and queue overflow at the parent node, child nodes are asked to decrease packet transmissions in two steps. | Parent must constantly estimate queue empty spaces and queue length thus increasing calculation overload in the node and depleted the battery faster. In addition, the high number of control packets transmitted by the parent node leads to more battery consumption. Another downside to this method is preventing child nodes from sending packets in times of congestion. |
| 2019 OFRRT-FUZZY [35] | In this method, three parameters of RSSI, residual energy, and throughput rate have been implemented as fuzzy inputs in the network. | Both link and node indicators have been considered. In this method delivery rate, latency, control overload, and energy consumption tests are better than the other two methods. | This method has only been compared to OF0 and MHROF objective functions and none of the recent methods have been considered. |
| 2019 ENRPL & OF-ER [36] | In this method, the node and link metrics have been suggested as a combined metric called CER. This compound metric includes link quality, queuing amount, node lifetime, latency and number of congested nodes. | This method has reduced packet loss and energy consumption by 37 and 46.5%, respectively, compared to the RPL method. In the OF-ER section in network consistency test, reliability and energy efficiency was better as compared to base objective functions. | This method has also only been assessed with the RPL base method and with OF0 and MHROF objective functions, thus its improvement over recent methods is not very significant. In addition, the network has not been assessed under different numbers of nodes and varieties of congestion. |

**TABLE 4.** *(Continued.)* **Advantages and disadvantages of recent methods on the RPL protocol.**

| | | | |
|---|---|---|---|
| 2019 OF-ECF [37] | This method is the improved OF-EC, which has combined three metrics, residual energy, ETX and forwarding latency, to make conscious parent selections. | This method performs better than OF-EC, OF0 and MHROF considering energy consumption. | Despite latency being one of the estimated parameters in this method, the authors have not provided any special test to assess the jitter and end-to-end latency rate of the packets. |
| 2019 LA-RPL [5] | In this paper, we have proposed a distributed method to balance the child node and reduce the congestion among the nodes in the network. In addition, each node has a learning automaton to perform the data aggregation and transmission from one node to another node. | This method performs better than RPL, BD-RPL, m-RPL, and A-RPL in simulation and experimentally tests such as Energy consumption, overhead packet, delay, lost packet, and throughput rate. | This method has not considered the trickle timer for DIO and inconsistency states. |
| 2020 PMFR [38] | In this method, a multicast mechanism based on the wireless shortest path heuristic (W-SPH) has been suggested to increase network lifetime. In addition, a proactive multicast forwarding with RPL (PMFR) method has been recommended to increase network reliability. | Based on the results, packet delivery rate has increased significantly and latency is about 50% less than previous studies. PMFR also decreases energy consumption by 40% compared to MPL networks. | There is nothing on the queue management of nodes in cases of congestion and collision. Considering that the network is multi-sink, the funnel effect has not been solved and the network is divided into several sub-networks, which is different from real-world applications. |
| 2020 NCRM [39] | This study is the optimized version of Sigma-ETX. In this method, ETX is not the only criteria for routing because it will cause a bottleneck. The total standard deviation (δ) of the route is estimated and a route with the least δ will be chosen. | This method performs better than others do in packet delivery rate, network lifetime, end-to-end latency and energy consumption. | Queue mechanism, management, and load balance have not been assessed in this method. On the other hand, control overload rates do not coincide with the results of the study. |
| 2020 QWL-RPL [40] | This method has been designed for networks with heterogeneous traffic rate. The Rank indicator in this method is derived from two metrics, number of remaining packets in line and number of node transactions in the recent duration. | Taking into account congestion and node queue status, which has a direct effect on network link forwarding, has led to a better performance in delivery rate, control overload rate and jitter latency tests compared to OF0 and MHROF objective functions. | In this method, the energy parameter, as a basic condition for increasing network lifetime, has been neglected. On the other hand, the energy consumption rate in this method is based on OF0 and has a higher convergence time compared to the other two objective functions. |
| 2020 CT-RPL [41] | The CT-RPL involves three processes, namely cluster formation, cluster head selection, and route establishment. The cluster is formed based on the Euclidean distance. The CH selection is accomplished using a game theoretic approach. Finally, the route is established using the metrics residual energy ratio (RER), queue utilization (QU), and expected transmission count (ETX). | CH selection is based on game theory approach, which efficiently rotate the CH node in the cluster and balance the energy effectively in the network. | In route establishment, CT-RPL is considered four metrics, which takes more time to calculate the best CH parent node. The time required to warm up the network has been somewhat long, and this has reduced the efficiency of the network. |

they become known and those with obtainable data and information are chosen.

- Determining the scoring method for indices: after determining the options and decision-making indicators, we must decide on the manner of scoring the indicators.
- Evaluating indicators: After determining the indicators and options and choosing the scoring method, we begin evaluating them.

- *Step 4:* Un-scaling: Every quantitative indicator has its own measurement scale, which makes it impossible to compare them with others; therefore, they must be somehow separated from the unit of measurement to make comparisons possible. To un-scale, we have utilized the linear un-scaling method in which the amount of negative indicators are reversed and then any value of the matrix is divided by the maximum value in its corresponding column. Therefore, in general we have:

  For positive indicators:

$$\sum_{ij} = \frac{a_{ij}}{Max\ a_j} \tag{1}$$

For negative indicators:

$$\sum_{ij} = \frac{\frac{1}{a_{ij}}}{Max(\frac{1}{a_j})} \tag{2}$$

It is obvious that $0 \leq n_{ij} \leq 1$ and the advantage of this un-scaling is that it is linear and all results become linear, therefore the relative order of available results remains the same.

- *Step 5:* After un-scaling the values for each indicator we must determine the relative importance of indicators in relation to each other which was carried out by least squares method. The main idea in this method rests on the fact that by using pair-comparisons of options the priority of each indicator is addressed. For this reason, the weighted paired matrix is created, the sum of values for each column is calculated and then each column element is divided by the sum values of the respective column. The newly obtained matrix is called the normalized comparison matrix. Finally, the mean value of each row is calculated in the normalized comparison matrix and a column matrix is obtained where its elements will be the weight of compared indicators.

$$\begin{array}{c|ccccc} & A_1 & . & . & . & A_n \\ \hline A_1 & 1 & . & . & . & . \\ . & . & 1 & . & . & . \\ . & . & . & 1 & . & . \\ . & . & . & . & 1 & . \\ A_n & . & . & . & . & 1 \end{array}$$

A .the initial output matrix

$$\begin{array}{c|ccccc} & A_1 & . & . & . & A_n \\ \hline A_1 & 1 & w_1/w_2 & . & . & w_1/w_n \\ . & w_2/w_1 & 1 & . & . & w_2/w_n \\ . & . & . & 1 & . & . \\ . & . & . & . & 1 & . \\ A_n & w_n/w_1 & . & . & . & 1 \\ \hline S & \sum_{i=1}^{i=n} w_{i,} & . & . & . & \sum_{i,j=1,n}^{n,n} w_{i,j} \end{array}$$

B. peer to peer weights and sum of each column

$$\begin{array}{c|ccccc|c} & A_1 & . & . & . & A_n & Average \\ \hline A_1 & \frac{1}{1} & . & . & . & \frac{w_1/w_n}{\sum_{j=1}^{n} w_{1,j}} & \frac{\sum_{j=1}^{j=n} w_{i,j}}{j} \\ . & . & . & . & . & . & . \\ . & . & . & . & . & . & . \\ . & . & . & . & . & . & . \\ A_n & \frac{w_n/w_1}{\sum_{i=1}^{n} w_{i,1}} & . & . & . & \frac{1}{1} & \frac{\sum_{i=1}^{i=n} w_{i,j}}{j} \end{array}$$

C. normalization and mean calculation of each row

$$\Rightarrow \begin{bmatrix} w_1 \\ w_2 \\ . \\ . \\ w_n \end{bmatrix}$$

D. weight obtained for each parameter

**FIGURE 1.** The process of computing the MCDM algorithm using AHP system.

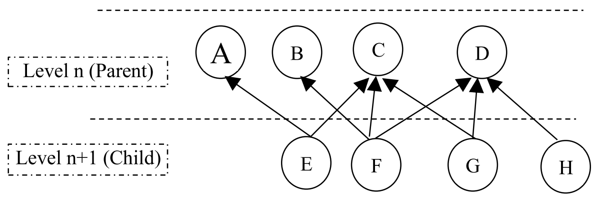
- *Step 6:* Comparing with the objective function and choosing the best option as the answer of the decision system.

$$Cost(k = 1 \ldots n) = \sum\nolimits_{k=1}^{n} (Param_i \times w_k) \tag{3}$$

$$Best\ Choise = Max\ (Cost_k) \tag{4}$$

## B. OF1 OBJECTIVE FUNCTION

The first phase of this project is dedicated to designing the first objective function (OF1) for creating the RPL network graph. In the RPL method, the child nodes are dependent on their single parent and this connection remains up until the link between parent and child is lost or the parent DIO's




| PL | Node |
|---|---|
| A,C | E |
| B, C, D | F |
| C, D | G |
| D | H |

**FIGURE 2.** The making and structure of the parent list in the child node.

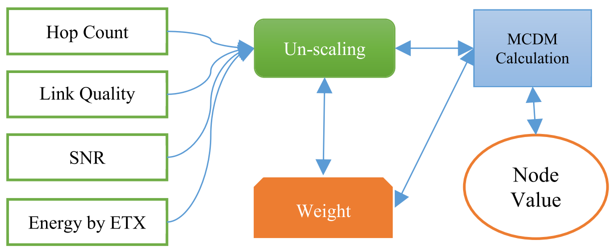



**FIGURE 3.** Multi criteria decision-making system in the OF1.

trickle timer expires. In the proposed method, the multi path method has been utilized so that each child node can connect to a fixed number of **Ω** parent nodes. In contrast to our previous method, the LA-RPL, where each parent node had a fixed number of **Ω** child nodes, now this condition happens in the child node. In this method, the graph-rating limit is the control and parent selection factor and the network has been modelled as a connected acyclic graph ***G(V,E)***. The **Ω** constant is $k < |V|$ and $|V|$ is the number of nodes in the network graph. Each node recognizes the **Ω** constant and this limit presents the number of acceptable parents. During the making of DODAG, each node v chooses the optimal parent(s) ***(p)*** for the parent list (***PL***), after computing the multi-criteria decision making system in the ***OF1***, and sends its request as a DAO. After each child node receives DAO-Ack from said parent(s), it adds them to its *PL* list. In this example and our proposed method the optimal number of $\Omega = 3$ is obtained (Figure 2).

Based on the mentioned metrics in section 3-2 of this paper, the considered criteria in the OF1 include the hop count from the parent to the root, link quality level (LQL), signal to noise ratio (SNR) and the expected energy expenditure (ETX). Finally, for computing the aforementioned parameters in the ***OF1*** output, reciprocal values were not used while calculating relative criteria due to similar proportions (Figure 3).

The first decision-making system parameters for making the network graph include:

- **Hop count (HC):** In the RPL network, the root node has an ***HC*** of zero and with each hop away from the root; a digit is added to the hop counter. In this regard, the amount of increase in rating is one unit.

$$HC\,(N) = Rank\,(Parent_{Node}) + Rank_{increase} \tag{5}$$

- **Link quality level (LQL):** contrary to many other factors, the ***LQL*** factor in a multi hop route is not cumulative (sigma) and must be computed separately for each link. In general, $Route_j\,(i, d)$ is the route from $\boldsymbol{i}$ to $\boldsymbol{d}$, from the parent node $\boldsymbol{j}$. This indicator is assessable by the incoming DIO signal in the child node and will be used during the making of the DODAG graph. The ***LQL*** is computed based on [43], which is modelled after the hardware specifications of the CC2430 microchip in real world.

$$LQL = (\text{CORR-a}) \cdot b \tag{6}$$

The result of this equation is from zero to 255. The value of $\boldsymbol{a}$ and $\boldsymbol{b}$ depends on the hardware and is modelled according to the CC2430 microchip datasheet in the simulator. The single hop cycle of ***LQL*** for each available parent is obtained from equation 7.

$$LQ(n) = Max\{LQ\,(n) + (LQ(n-1) * \theta)\} \tag{7}$$

where the best value for $\boldsymbol{\theta}$ is 0.20. In other words, the parent node's link quality can ultimately add 20 percent to the parent node value.

- **Signal to noise ratio (SNR):** in order to estimate the ***SNR***, we used the proposed model by [43], [44]. This model is based on simple calculations relative to the sensor node while retaining the base model's accuracy. The ***SNR*** is a concave indicator (the ***SNR*** of one route is limited by a link that has the maximum amount of available signal to noise ratio). It is therefore desirable to avoid choosing a node with a low ***SNR***; as choosing, an inappropriate link and a high amount of noise in the link will lead to increased packet loss in the network and somewhat wastes resources (energy and time). The maximum value for SNR between source and destination [45] is obtained by equation 8:

$$\mathrm{SNR_{ijd}} = \max\left\{\frac{\text{Signal}}{\text{Noise}_{\,(l)}}\right\}, \quad \forall \mathrm{l} \in \mathrm{route_j\ (i, d)} \tag{8}$$

where $Route_j(i, d)$ is the route from $\boldsymbol{i}$ to $\boldsymbol{d}$ via $\boldsymbol{j}$. In order to prevent the greedy selection of a single hop parent, we have used a higher single hop indicator with the respected parent based on the ***LQ*** parameter, which resulted in the best value (0.20) for $\boldsymbol{\theta}$. Therefore, the link ***SNR*** between child node and its parent is obtained via equation 9.

$$SNR(n) = Max\{SNR\,(n) + (SNR(n - 1 * \theta)\} \tag{9}$$

- **Energy expenditure rate per expected link transmission ($\mathbf{E}_{ETX}$):** the energy expenditure of the expected link transmission $\boldsymbol{ETX_{link}}$, in the RPL network, has different definitions each of which is determined based on the network goals. The most common ETX definition is the admission capacity or route cost which is obtained from equation 10.

$$ETX = \frac{1}{d_f \times d_r} \tag{10}$$

The delivery forward ratio (***df***) equals the probability that a data packet successfully reaches its destination and the reverse delivery ratio (***dr***) is the probability that the ACK packet is successfully received at the packet-sending node. It must be taken into account that ETX is in fact the mathematical expectation for the number of required transmissions (including re-transmissions) to deliver a packet to its destination.

Based on this, using the ETX metric, an estimate of link loss ratio can be obtained. This estimation is obtained from 11:

$$ETX_l = \frac{1}{(1 - d_f) \times (1 - d_r)} \tag{11}$$

In this equation, ETX calculates the information for link loss ratio in any direction. If the link is asymmetric or unilateral, the value for ***dr*** is zero. On the other hand, the expected ETX energy expenditure and the residue energy rate of the node is estimated during the same transfer and enters the decision making system; however, based on the aim of this study, we are looking to estimate energy expenditure per packet transfer in the RPL network and its dependency on ETX, which is obtained from equation 12 (***P*** is energy expenditure, $\boldsymbol{\lambda}$ is link transfer rate, ***L*** is packet size) [42], [46].

$$E_{ETX} = ETX \times Pl \times \frac{L}{\lambda l} \tag{12}$$

### C. OBJECTIVE FUNCTION OF2

The second phase of this study is dedicated to designing the objective function ***OF2***. We have proposed a decision-making system aware of service quality by taking into account indicators and parameters that are influential in link quality and network energy consumption. When the decisions facing a network are based on one metric, decisions are made greedily which is not suitable in most applications. Service quality in low power and lossy networks in the internet of things has various parameters and definitions, which often contain several metrics, and every decision must be made by considering several indicators. Therefore, various solutions have been proposed as objective functions based on a fuzzy system or mathematical membership functions, to result in choosing the correct alternative. The main problem with most previous methods has two aspects:

1- Metrics are only towards the node or they are links.

2- Metric weights in their proposed system are constant during network operation.

In this study, by covering both above-mentioned issues, we have introduced, as innovations of the current study, the multiple combination of node and link metrics and the dynamic weight of metrics. The parameters in the second decision-making system in quality of service-aware routing include:

- **Battery Depletion Index (*$BDI_i$*):** The node energy expenditure is one of the important factors in quality of service-aware routing in the RPL network; because, as a result of early energy depletion in the node, its connection with other nodes in the network is lost and the node dies. Therefore, during routing in the proposed decision-making system the battery depletion index can be obtained from the remaining energy. In equation 13, $E_{current}$ is the current energy of the node and $E_{initial}$ is the initial amount of energy in the node [12].

$$RER_i = \frac{E_{current}}{E_{initial}} \tag{13}$$

However, the battery depletion index for node $i$ is calculated from equation 14.

$$BDI_i = (1 - RER_i) \tag{14}$$

- **Node's Queue Status Index ($QSI_i$):** The effective index for determining node value in the RPL network is the node's queue status ratio in a specified time, which has a direct relation to the network traffic load. In a node, the size of the queue buffer for buffering, processing and sending a packet is constant and specified. It is obvious that when the input and output rates of the queue are not compatible it will lead to an overflow of the node buffer in the network. This index is calculable like the queue status index introduced in the previous study [42].

$$QSI_i = \frac{\sum_{i=1}^{10} queueingPacket\ (i) + \sum_{i=11}^{20} 2 \times queueingPacket\ (i)}{15} \tag{15}$$

The output from equation 15 can determine the node status. If the result is more than 0.7 it means the node is likely to face congestion and overflow in the near future. The node queue status index obtained from this equation must be calculated periodically (every second) in the node.

- **Link Latency Index ($LDI_i$):** Latency in each network node in the RPL structure includes link latency, queue latency, processing latency and the latency in forwarding the packet. Indeed, similar to the node queue index, this index is also directly related to network traffic rate per unit time. The latency for each parent $p$ or child $i$ are obtained separately by equation 16 and the link latency index is calculable via equation 17.

$$NodeDelay_i = Proc_{Delay_i} + Queue_{Delay_i} + Trans_{Delay_i} + Prop_{Delay_i} \tag{16}$$

$$LinkDelayIndex_i^p = \sum Delay_i^p \tag{17}$$

- **Node's Throughput Index ($TI_i$):** This index is the number of bytes, which are transmitted by a specific parent node in the network during a specific alternation period. Network node transmission is one of the most important indicators for evaluating the internet of things network based on quality service, and is calculated by equation 18.

$$Throughput\ Index_p = \frac{((Size_{data}) \times (time_{taken\_data\_transmitting}))}{Response_{time}} \tag{18}$$

#### 1) UPDATING PARAMETER WEIGHTS WITH THE LEARNING AUTOMATA

As mentioned in section 3-3, the main innovation of this research is the dynamic weight of combined parameters in the ***OF2***. In other words, in the second decision-making system, link and node parameters are combined and the weight of each parameter in the network must be variable depending on the network time and traffic changes. Because of the random distribution of nodes in the network and the inability to calculate traffic levels in different sections, considering parameter weight as a constant is incorrect. On the other hand, it is not possible to accurately calculate these weights since we are faced with an NP-Hard problem. Therefore, we have proposed a random learning automata system for this stage so to update parameter weights according to time and traffic changes in the network and by doing so we increase network lifetime and satisfy other quality service indices. The system learning process has become a favourable research topic in recent years, which usually aims to provide a methodology for learning principles within a machine. Learning is defined as changes in the efficiency of a system based on experiences. An important property of learning systems is the ability to increase efficiency in time. From a mathematical perspective, the aim of a learning system is to optimize a function (duty) which is not completely known. Thus, an approach to this matter is to reduce the goals of the learning system to an optimization problem, which is defined on a collection of parameters, and its aim is to find the optimum parameters. A learning automaton can be considered as an individual object with finite actions. The learning automata operates by choosing one function from its collection of functions and applying it to the environment. A random environment evaluates this action and the automata uses this response to choose its next action. During this process the automata learns to choose the optimum action. The automata-learning algorithm [47] determines the process by which the automata uses the environment's response to choose its next action. A learning automaton consists of two main parts [48]:

- A random automaton with a finite number of actions and a random environment, which the automata is connected to.
- The learning algorithm, which the automata uses to learn the optimized action.

A random automata is defined as a 4-tuple $\boldsymbol{LA} \equiv \{\boldsymbol{\alpha}, \beta, p, T\}$ where $\boldsymbol{\alpha} \equiv \{\boldsymbol{\alpha_1}, \boldsymbol{\alpha_2}, \ldots, \boldsymbol{\alpha_n}\}$ is the actions of the automata ($\boldsymbol{n}$ is the number of actions) and $\boldsymbol{\beta} \equiv \{\boldsymbol{\beta_1}, \boldsymbol{\beta_2}, \ldots, \boldsymbol{\beta_m}\}$ is the inputs of the automata. The environment can be shown as a 4-tuple $\boldsymbol{E} \equiv \{\boldsymbol{\alpha}, \beta, c, d\}$ where $\boldsymbol{c} \equiv \{\boldsymbol{c_1}, \boldsymbol{c_2}, \ldots, \boldsymbol{c_n}\}$ is the set of possible penalties and $\boldsymbol{d} \equiv \{\boldsymbol{d_1}, \boldsymbol{d_2}, \ldots, \boldsymbol{d_n}\}$ shows the automata's rewards. The environment input is one of the $\boldsymbol{n}$ number of actions chosen by the automata. The

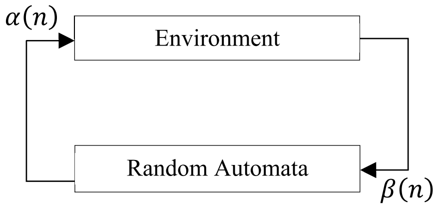



**FIGURE 4. The Stochastic Learning Automata [49].**

environment output (response) to each action $\boldsymbol{i}$ is determined by $\boldsymbol{\beta_i}$. If $\boldsymbol{\beta_i}$ is a binary response, the environment is called a P-model. In such an environment $\boldsymbol{\beta_i}\,(\boldsymbol{n}) = \mathbf{1}$ is considered an unfavorable response or failure and $\boldsymbol{\beta_i}\,(\boldsymbol{n}) = \mathbf{0}$ is a favorable response or success. The set $\boldsymbol{c}$ determines the possibility of penalties of environment responses and is defined by equation 19:

$$c_i = Prob\,\{\beta\,(n) = 1|\alpha\,(n) = \alpha_i\}\,, \quad i = \{1, 2, 3, \ldots, n\} \tag{19}$$

Which shows the probability of action $\boldsymbol{\alpha_i}$ receiving an unfavourable response from the environment. The $\boldsymbol{\alpha_i}$ values are unknown and $\boldsymbol{c_i}$ are considered to have a unique minimum. Therefore, the environment can be presented with the probability set of rewards (success) $\{\boldsymbol{d_i}\}$ where $\boldsymbol{d_i}$ is the probability of receiving a favourable response to the action $\boldsymbol{\alpha_i}$. The random automata's relation to the environment is presented in figure 4. This set, alongside the learning algorithm, is called the Stochastic Learning Automata. Accordingly, the Stochastic Learning Automata can be shown as a 4-tuple $\boldsymbol{LA} \equiv \{\boldsymbol{\alpha}, \beta, p, T\}$, $\boldsymbol{p} \equiv \{\boldsymbol{p_1}, \boldsymbol{p_2}, \ldots, \boldsymbol{p_n}\}$ is the automata actions probability vector and $\boldsymbol{T} \equiv \boldsymbol{p}\,(\boldsymbol{n}+\mathbf{1}) = \boldsymbol{T}[\boldsymbol{\alpha}\,(\boldsymbol{n})\,, \boldsymbol{\beta}\,(\boldsymbol{n})\,, \boldsymbol{p}\,(\boldsymbol{n})]$ is the learning algorithm.

If in the $\boldsymbol{n^{th}}$ step $\boldsymbol{\alpha_i}$ action is selected, thus in the $\boldsymbol{n^{th}}+\boldsymbol{1}$ step we will have:

a) The favourable response from the environment:

$$P_{i,j}\,(n+1) = \begin{cases} P_{i,j}\,(n) + \alpha\left(1 - P_{i,j}\,(n)\right), & i = j \\ P_{i,j}\,(n)\,(1-\alpha)\,, \forall j, & j \neq i \end{cases} \tag{20}$$

b) The unfavourable response from the environment:

$$P_{i,j}\,(n+1) = \begin{cases} P_{i,j}\,(n) + (1-\beta)\,, & i = j \\ \frac{\beta}{r-1} + P_{i,j}\,(n)\,(1-\beta)\,, & \forall j, j \neq i \end{cases} \tag{21}$$

The $\boldsymbol{\alpha}$ set includes automata outputs (actions) which the automata chooses one actions from $\boldsymbol{r}$ actions in the set to apply to the environment. The $\boldsymbol{\beta}$ set of inputs determines the automata inputs [48].

The learning automata is a decision-making system, which determines the necessary policy for choosing one of its actions based on the feedback received from the environment. The learning automata consists of two phases, the selection phase and the learning phase. In the selection phase it makes decisions, based on feedback from the environment, to optimize compared to previous periods [49].

- Selection phase: All the parameters of the sensor node have a threshold label ( ***lbl-Threshold***) which is valued

of its actions based on

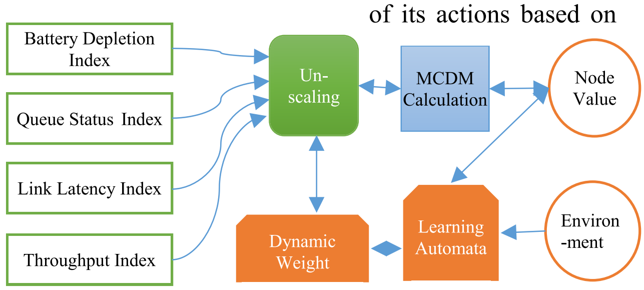



**FIGURE 5. A schematic of the proposed decision making system in the second objective function using the learning automata.**

at zero for all the node metrics at the beginning of the network operation. However, after $\boldsymbol{t}$ time spent, changes will occur in the network traffic and node energy levels and if they are in our permitted ranges the value zero will remain, but if any of the parameters enter the restricted range (outside of the problem answer) the ***lbl - Threshold*** $= \boldsymbol{1}$ and the condition to enter the automata has happened. In the beginning of the operation all, the nodes have the same $\boldsymbol{S_w}$, but after repeating the algorithm and receiving reinforcement signals from the environment this value changes.
- For the learning phase, the learning automata is used as a distributed agent in the RPL network. Each sensory node, as a learning agent, is equipped with learning automata, which has two different functions. The concepts and parameters of the learning automata is described as below:
  - Agent: each sensor node, which acts as an individual learner, which means the learning agent's action, has no effect on other learning agents.
  - Action: an agent can act as a variable weight or fixed weight.
  - Reinforcement Signal ($\boldsymbol{S}$): the number of parameters exiting the answer range by the parent node $\boldsymbol{j}$ in the time period t (input degree). $\boldsymbol{\vartheta}$ Equals the number of metrics.

(22) and (23), as shown at the bottom of the next page. If $\mathbf{S{>}Threshold}\boldsymbol{\gamma}$, the node $\boldsymbol{j}$ is awarded otherwise it is penalized. If it receives an award, $\boldsymbol{P_w}$ changes as follows:

$$P_w = P_w + \alpha \times R{\times}(1{-}P_w) \tag{24}$$

An in case of receiving a penalty:

$$P_w = (1-\beta\,(1-R))P_w \tag{25}$$

$\boldsymbol{\alpha}$ is the coefficient of award, $\boldsymbol{\beta}$ the coefficient of penalty and for each $\boldsymbol{P_{w_i}}$ the changes in probability equals the sum of $\boldsymbol{\vartheta} - \mathbf{1}$ parameters, which is modelled in equation 26.

$$P_{w_i} = 1 - (\sum_{i=1}^{\vartheta-1} P_{wi}) \tag{26}$$

In Figure 6, $\boldsymbol{LT_{min}}$ equals the minimum determined lifetime of the node, $\boldsymbol{LT_{max}}$ is the maximum determined lifetime of the node, $\boldsymbol{T}$ is the simulation time, $\boldsymbol{LT_C}$ is the lifetime

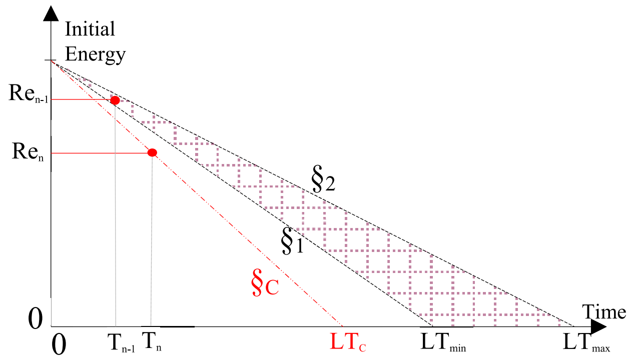



**FIGURE 6.** A schematic of the problem's answer in regards to the remaining energy parameter during sampling.

with the current energy consumption, $\boldsymbol{Re_{n-1}}$ is the remaining energy in the previous sampling $\boldsymbol{T_{n-1}}$, $\boldsymbol{Re_n}$ is the remaining energy in the node at the current sampling time, $\S_2$ is the problem's maximum answer length, $\S_1$ is the problem's minimum answer length, and $\S_C$ is the segment length of the current sample.

The answer to the problem is located in the striped region so that the automata system tries to keep the node's remaining energy in this range by giving penalties or awards to parameter weights in the system. Calculating the answer to the problem is possible via equations 27 to 30.

$$\S_2 = \sqrt{IE_{max}^2 + LT_{max}^2} \tag{27}$$

$$\S_1 = \sqrt{IE_0^2 + LT_{min}^2} \tag{28}$$

$$\S_1 \leq Answer\ range \leq \S_2 \tag{29}$$

The line $\boldsymbol{m}$ slope for two points is obtained as below:

$$Y = mX, m = \frac{y_2 - y_1}{x_2 - x_1} \tag{30}$$

Finally, the line slope for $\S_C$ is obtained and the intersection of line $\S_C$ with the axis $\boldsymbol{T}$ which is $\boldsymbol{LT_C}$ is derived. Both the length of the $\boldsymbol{LT_C}$ segment and the rate of $\boldsymbol{Kc}$ line slope, which only inverts the condition for entering the automata, can be measurement criteria. To enter the automata, the $\S_C$ line slope must be higher than the threshold slope for $\S_1$ or lower than the threshold slope for $\S_2$. In other words, the aim is for the line slope of $\S_C$ to fall between the slopes of two lines $\S_1$ and $\S_2$. Therefore, the death of the first node is latency and idle nodes or those with less traffic load will have greater participation.

## IV. SIMULATION AND PRACTICAL TEST RESULTS

In the present research, we have established our simulation on the RPL routing protocol in an environment with randomly

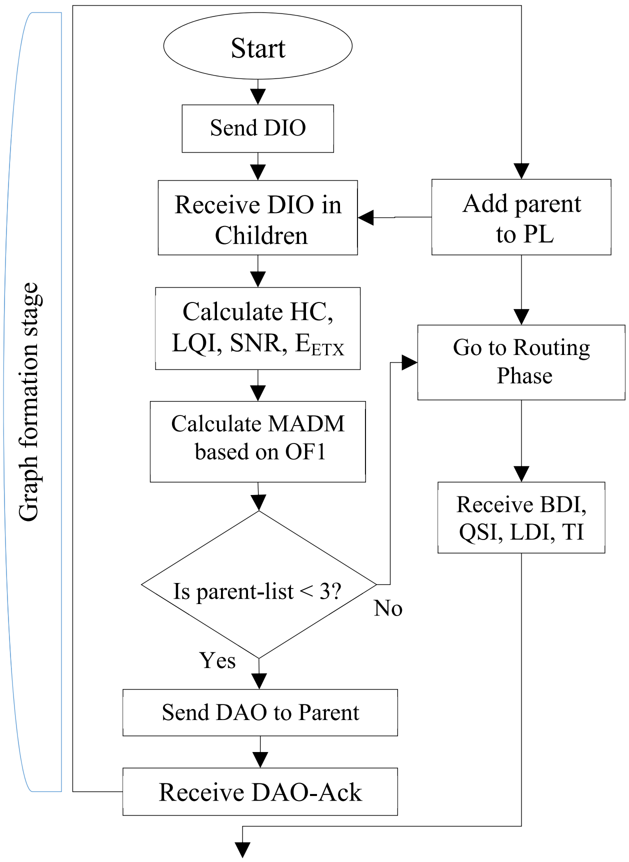



**FIGURE 7.** The complete diagram for the proposed method in two phases, graph formation and routing.

distributed sensor nodes and a centralized well node. This simulation was implemented in an NS2.35 environment, and the results of the simulation obtained from 20 repetitions of algorithms and the variance calculation are presented in the remainder of this chapter based on the type of test. The algorithms simulated and compared in this study include the following methods OF-FC, PMFR, NCRM, QWL-RPL, CT-RPL, and the proposed DDSLA-RPL algorithm, which have all been discussed in sections two and three of this paper. In Table 5, parameters considered in the simulation of the proposed method are presented. In the tests carried out to compare the proposed method and five other methods, the amount of entry traffic is considered $\lambda = 1$ and for more precise evaluation the proposed method was compared with two different traffic scenarios i.e. $\lambda = 0.6$, 0.8, and 1.

In order to evaluate the correct performance of the proposed algorithm compared to other algorithms in this study, each test was repeated 20 times and the variances of results were recorded. The variance was calculated using equation

$$Rate\ j = [\frac{(EC_r - EC_{r-1}) + (Q_r - Q_{r-1}) + (D_r - D_{r-1}) + (Thr_r - Thr_{r-1})}{\vartheta}] \tag{22}$$

$$S = 1 - 1/Rate\ j \tag{23}$$

**TABLE 5.** Units for magnetic properties.

| Parameter | Value |
|---|---|
| Number of nodes | 50, 75, 100 Homogeneous sensor nodes |
| Initial energy of nodes | 5 Joule |
| Number of root/sink | 1 by randomly location |
| Energy of root/sink | Unlimited |
| Distribution of nodes | Randomly |
| Area | Square region of 100 |
| The nodes' radius | 30 meters |
| The transmission rate | 250 kbps |
| Traffic type | UDP(CBR) |
| Traffic | An exponential distribution function |
| Packet inter-arrival time | $\lambda = 0.6 \sim 1$ per second |
| CW size | 1~63 |
| The total buffer size | 10 data packets |
| Size of packets | 50 bytes |
| MAC and PHY layer | IEEE 802.15.4 standard version |
| Simulation time | 500 second |
| Number of iteration | 20 times |

* The average arrival time of packets is based on the Poisson distribution.

31 in which n = 20 the number of algorithm runs. $\mu$ in each level equals the average value of the number of test repetitions.

$$\delta = \sqrt{\frac{1}{N}\sum\nolimits_{i=1}^{n}(x_i - \mu)^2} \tag{31}$$

The evaluation metrics include:

- Average network lifetime: it is the predetermined average network lifetime and its realization rate per unit time.
- Energy efficiency and consumption balance: the amount of balance and fairness in nodes' energy consumption rates.
- Correlation graph consistency: the average changes to the parent node in each net-work, which is a sign of network consistency or inconsistency.
- Transmission latency: the average time spent for receiving, processing, queuing, transmission and distribution of packets between child and parent.
- Route forwarding: the rate of transferred bytes per unit of time spent for network packet transactions.
- Packet delivery rate: this metric refers to the proportion of received packets to delivered ones.
- Control messages: the sum of control packets during network operation time, which include DIO, DAO, DIS and DAO-Ack.

### *A. AVERAGE NETWORK LIFETIME TEST*

This test is for evaluating the lifetime of the proposed protocol and its parallel proto-cols under the influence of graph formation, optimal route selection, and energy consumption balance in the network. By intelligent and correct use of the proposed decision-making system and by considering the effective parameters energy consumption rate and network resource consumption have been balanced. This means that the topology of the network nodes is more sustainable and stable compared to other methods and that the network will not fail as easily from link quality issues or energy loss. One of the ways to calculate average network lifetime is by using the death of the first node criterion. The more the death of the first node is latencies it shows the higher efficacy of the method in creating balance and resolving hotspots or energy consumption. The time of death for the first nodes in the evaluated protocols is presented in Table 6.

**TABLE 6.** The time of death for the first node in the network in parallel protocols with 50, 75 and 100 nodes.

| Networ k Size | OF-EC | PM FR | NCR M | QWL-RPL | CT-RPL | DDSLA-RPL |
|---|---|---|---|---|---|---|
| 50 | 387 | 376 | 409 | 422 | 439 | 493 |
| 75 | 302 | 320 | 309 | 347 | 336 | 489 |
| 100 | 255 | 249 | 266 | 270 | 288 | 477 |

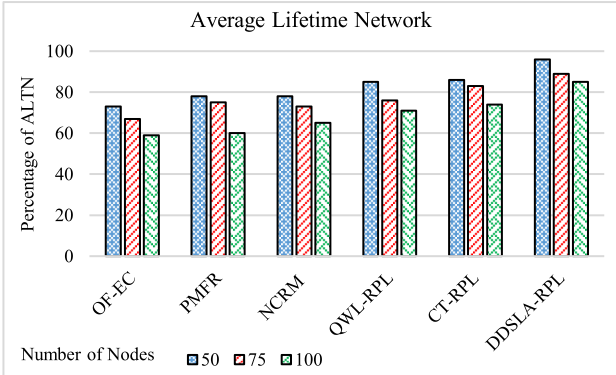



**FIGURE 8.** The diagram for average network lifetime during 20 iterations of tests with an entry traffic of one packet per second.

**TABLE 7.** The diagram shows the time of death for the first node in the proposed DDSLA-RPL protocol at different traffic rates.

| Network Size in DDSLA-RPL | Packet inter-arrival time | | |
|---|---|---|---|
| | $\lambda = 0.6$ s | $\lambda = 0.8$ s | $\lambda = 1$ s |
| 50 | 437 | 456 | 493 |
| 75 | 393 | 421 | 489 |
| 100 | 311 | 386 | 477 |

The time of death for the first node and the average lifetime network (ALTN) is obtained from equation 32 [50]:

$$ALTN = \frac{\sum_{i=1}^{N-m} t_i + (m \times T)}{N} \tag{32}$$

where $t_i$ is the time of death for the $i^{th}$ node, $N$ is the total number of nodes in the network, $m$ the number of surviving nodes at the end of the simulation and $T$ is the predetermined network lifetime.

Also presented in table 7 is an evaluation of the time of deaths for the first node in different traffics.

**TABLE 8.** Node energy consumption variance in different methods.

| Network Size | OF-EC | PMFR | NCRM | QWL-RPL | CT-RPL | DDSLA-RPL |
|---|---|---|---|---|---|---|
| 50 | 37.45 | 36.04 | 35.22 | 36.34 | 37.11 | 42.17 |
| 75 | 37.27 | 37.77 | 36.87 | 37.18 | 39.83 | 45.03 |
| 100 | 39.16 | 38.45 | 37.07 | 38.55 | 41.28 | 47.8 |

## B. ENERGY EFFICIENCY AND FAIRNESS

Data transmission and network efficiency is usually affected by the node energy consumption in Low power and Lossy networks and this is a major concern. Therefore, one of the important goals in the RPL network, because of limited resources such as node energy, is the balanced energy consumption per node in the network. The more the energy consumption slope falls within the permitted range the higher the node lifetime is and the network does not face early node death. The three important factors that are used to evaluate network energy efficiency are average energy balance, fairness and lifetime in nodes; however, before calculating energy consumption fairness, the standard formula to calculate energy in this study is according to equation 33.

$$E_{tx}(m, d) = (E_{con} \times m) + )t_{amp} \times m \times l^2) \quad (33)$$

where $\boldsymbol{E_{con}}$ is energy consumption, $\boldsymbol{l^2}$ is energy loss, and the distance between node and parent is $\boldsymbol{d}$. The amplifying value for node transmission is $\boldsymbol{t_{amp}}$ and $\boldsymbol{m}$ is the transferred bits between child and parent. Finally, based on equation 34, average energy level is the proportion of remaining energy in all nodes after complete simulation to the total initial energy of the nodes. As can be seen, the proposed method has several advantages compared to other methods which has led to satisfying results in this test. The energy consumption variance is obtained via equation 34 and nodes' energy consumption fairness is calculated via equation 35.

$$Dev = \sum\nolimits_{i=1}^{n} (energy_i - Average)^2 \quad (34)$$

If the result of equation 35 is closer to 100 percent, it shows fairness in node energy consumptions. $\boldsymbol{Dev_{worst}}$ is the worst situation where half of the nodes have spent their energy and the rest have no energy consumption.

$$Fairness = \frac{1 - Dev}{Dev_{worst}} \quad (35)$$

In Table 9, the fairness indicator is presented for the proposed DDSLA-RPL protocol at variable traffic rates. Based on the obtained results, the fairness indicator is directly related to the number of nodes in the network. The higher number of nodes in the network leads to higher possibility of fairness in the network because the system has more options to choose from; though this indicator is inversely related to the network traffic and with increasing network traffic, energy consumption fairness in nodes decreases.

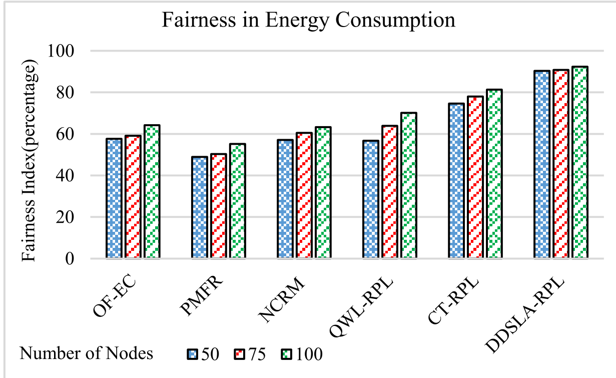



**FIGURE 9.** The nodes' energy consumption fairness indicator during 20 iterations of tests with an entry traffic of 1 packet per second.

**TABLE 9.** The nodes' energy consumption fairness indicator for the proposed DDSLA-RPL protocol at variable traffic rates.

| Network Size in DDSLA-RPL | Packet inter-arrival time $\lambda = 0.6$ s | $\lambda = 0.8$ s | $\lambda = 1$ s |
|---|---|---|---|
| 50 | 81.12 | 87.11 | 92.38 |
| 75 | 73.78 | 83.56 | 90.86 |
| 100 | 65.25 | 78.14 | 90.34 |

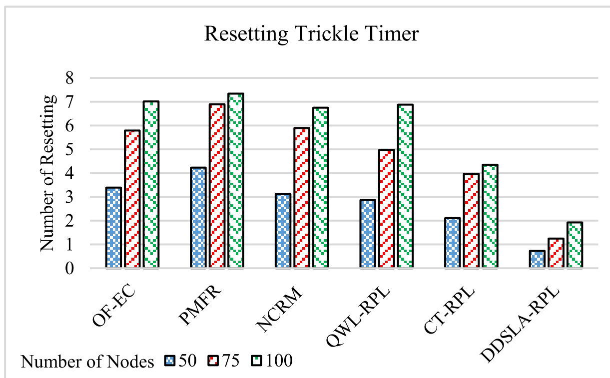



**FIGURE 10.** Average network consistency test during 20 test rounds with incoming traffic of 1 packet per second.

## C. NETWORK GRAPH ALIGNMENT CONSISTENCY TEST

The network tree is susceptible to change under two conditions; the first is from decisions or regulations which are made during the construction of network graph or tree. If the network tree is made with reliability, considering the link, then it possibly has a high consistency and faces fewer local or global repairs; or in other words, the inconsistency count in the node's trickle timer does not reach the fixed coefficient of k. The second condition is the effect of balance and equalization in the routing energy consumption for RPL network nodes. Quality of service aware routing and using the multipath method but limited to the parent list for the nodes has been successful in preventing early death in parent nodes.

**TABLE 10.** Average number of node's trickle timer resets in the proposed method with variable traffic.

| Network Size in DDSLA-RPL | Packet inter-arrival time $\lambda = 0.6$ s | $\lambda = 0.8$ s | $\lambda = 1$ s |
|---|---|---|---|
| 50 | 0.99 | 0.81 | 0.73 |
| 75 | 1.46 | 1.39 | 1.25 |
| 100 | 2.57 | 2.31 | 1.93 |

**TABLE 11.** Average node latency in the proposed method based on the variable packet entry rate.

| Network Size in DDSLA-RPL | Packet inter-arrival time $\lambda = 0.6$ s | $\lambda = 0.8$ s | $\lambda = 1$ s |
|---|---|---|---|
| 50 | 2.45 | 1.78 | 1.29 |
| 75 | 3.41 | 2.74 | 2.14 |
| 100 | 4.04 | 3.33 | 2.63 |

According to Figure 10, as obtained from the results of the simulation, the proposed DDSLA-RPL algorithm significantly outperforms the other five methods in the 50 to 100 node counts.

In addition, in Table 10, the proposed protocol was tested on variable traffic of $\lambda = 0.6 \sim 1$ which with the increase of traffic rate in the network, the level of consistency decreased at a reasonable rate, which was a predictable phenomenon.

### D. AVERAGE NODE LATENCY

Based on different definitions provided in the field of networking, the latency criteria is the amount of time it takes the packet to be transferred from the source to its full delivery at the destination. In some methods, this criteria is calculated as end-to-end and cumulative; but in the proposed method, latency was analysed as step-by-step so that the latency for a packet includes the sum of all the node processing, queue, transfer and distribution latencies and the lower this rate is the lower the end-to-end latency of the network will be. Numerous factors and metrics, including hardware and software impact the latency rate in every node which have all been taken into account in the proposed method to limit the probability of latencies. Factors such as noise, link quality, retrying to access media, node queue status, and node latency and forwarding rates, were all taken into account in the form of two decision-making systems with variable weights that are constantly updated by the learning automata. According to the figure, the multi-criteria decision system for network graph formation and quality of service aware routing with dynamic parameter weights has had significant efficiency in reducing latency and the number of exchanges and retransmission between nodes. To calculate latency rate equations 16 and 17 in section 3-3 of this paper were used.

In Figure 11, the traffic rate has been set at 1 packet per second and in case of testing for other methods with lower incoming packet rates, their results would be worse than those in Table 9.

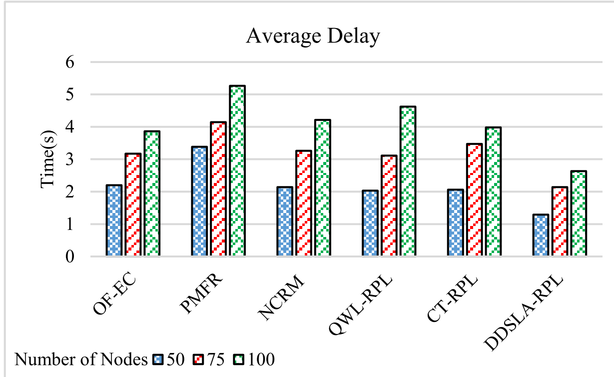



**FIGURE 11.** Graph of average network latency during 20 test rounds with an incoming traffic of 1 packet per second.

The average latency for the proposed DDSLA-RPL method with a packet incoming rate of $\lambda = 0.6$ to $\lambda = 1$ is presented in Table 9. As expected, with reduced packet entry distances, the node latency increased.

### E. JFI TEST FOR LINK THROUGHPUT

To calculate Jain's Fairness Index (JFI) for allocating network resources for forwarding links between nodes, the link throughput must first be calculated. The link throughput in the network may depend on many factors, which often face challenges such as increased traffic load, link loss, network queuing, bandwidth reduction, current rate imbalance between transmitter and receiver, congestion and collision in the receiver. Therefore, in the proposed DDSLA-RPL method our aim was to decrease these challenges as much as possible by using the decision system to create consistent links with suitable parents with a maximum of three parents for each child node in the network graph formation stage. Then in the routing stage, a multi-route, quality of service aware routing method was proposed which calculates and updates the weight of effective parameters in the decision system at specified intervals. Therefore, this dynamic has caused the throughput of the nodes to be maintained as much as possible by applying load balancing. The throughput of child link $\boldsymbol{i}$ and parent $\boldsymbol{p}$ can be calculated through Equation 36. Also calculated through Equation 37 is the amount of fairness (JFI) in allocating network resources such as bandwidth to network nodes, where $\boldsymbol{Th_i}$ is the throughput of child link $\boldsymbol{i}$ and parent $\boldsymbol{p}$. Also n is the number of nodes in the network.

$$Throughput_{i,p} = \frac{\sum_{i=1}^{n} ((size_{data}) \times (time\_taken_{data\_transmitting}))}{(Response_{time}) \times n} \tag{36}$$

$$JFI_{Th} = \frac{[\sum_{i=1}^{n} Th_i]^2}{n \sum_{i=1}^{n} (Th_i)^2} \tag{37}$$

In Table 12, the average fairness rate JFI has been implemented in the network nodes' throughput for incoming traffic rates of $\lambda = 0.6$ to $\lambda = 1$. As expected, with increasing

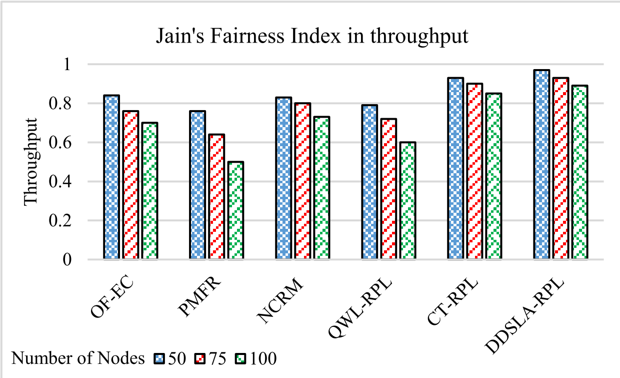



**FIGURE 12.** Average node link throughput in the network during 20 test rounds with an incoming traffic of 1 packet per second.

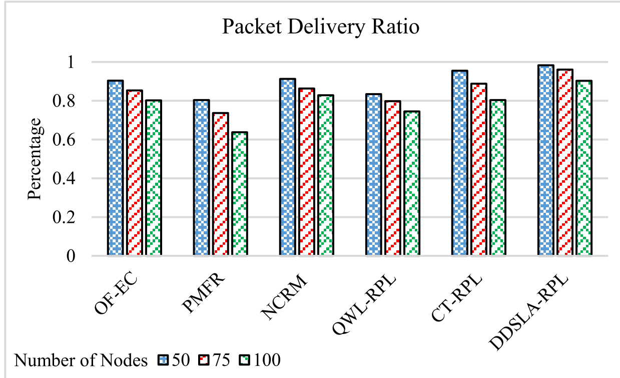



**FIGURE 13.** Average packet delivery rate during 20 test rounds with incoming traffic of 1 packet per second.

**TABLE 12.** Fairness in the throughput of the network nodes in the proposed DDSLA-RPL protocol with variable traffic.

| Network Size in DDSLA-RPL | Packet inter-arrival time | | |
|---|---|---|---|
| | $\lambda = 0.6$ s | $\lambda = 0.8$ s | $\lambda = 1$ s |
| 50 | 0.88 | 0.94 | 0.97 |
| 75 | 0.82 | 0.9 | 0.93 |
| 100 | 0.76 | 0.86 | 0.89 |

**TABLE 13.** Network packet delivery rate in the proposed DDSLA-RPL protocol with variable traffic.

| Network Size in DDSLA-RPL | Packet inter-arrival time | | |
|---|---|---|---|
| | $\lambda = 0.6$ | $\lambda = 0.8$ | $\lambda = 1$ |
| 50 | 0.921 | 0.943 | 0.983 |
| 75 | 0.887 | 0.902 | 0.961 |
| 100 | 0.822 | 0.863 | 0.903 |

number of nodes and decreasing packet production gaps the network throughput decreased; but the important point is that in the proposed DDSLA-RPL method, despite increased traffic load, throughput rate did not decrease significantly, which shows that the proposed method is capable of performing well in higher traffic rates.

### *F. PACKET DELIVERY RATE TEST*

In the RPL tree structure, the packet delivery rate depends on numerous factors but the most important challenges in the way of this tree structure are link failure, congestion rate and possible collisions in the network, which can greatly affect the packet delivery rate to a great extent. In the DDSLA-RPL method, the graph formation phase with the proposed decision system has managed, to a great extent, create high quality and consistent links. On the other hand, using the multi-route mechanism has enabled the child nodes to choose another parent from the list of available parents in times of congestion or parent quality loss. This option delays the time of death for the node and also prevents the parent node's buffer overflow as much as possible. Updating the parent node status and adjusting parameter weights with the learning automata for calculating the final value of the node has been able to optimally maintain the packet delivery rate in a 500 second simulation period. The reduced rate of packet loss in the network has eliminated the need for resending packets in the direction of the root. This fact has improved the efficient network operation time for data transfer.

Table 13 shows the delivery rate of network data packets during variable incoming traffic. Obviously, the capacity of the data exchange rate in the network depends on the hardware and the communication channel, and as the traffic rate and the number of nodes in the network reaches the threshold point, the throughput capacity will increase. However, by exceeding the network capacity threshold, this rate will gradually decrease.

### *G. THE NUMBER OF CONTROL PACKET TEST*

A high rate of network time is always spent exchanging control messages in the RPL tree structure, because any connection in RPL requires sending a control packet. On the other hand, in the tree structure of the network and in not so large-scale environments the rate of collision or signal collision of nodes in the network will be high due to the use of common wireless communication media. Therefore, accelerating the stability of the network graph, preventing lossy communications, will reduce resending at a favourable rate. However, considering that in the proposed DDSLA-RPL method, we have used the CC control message as a factor to update the weight of the parent node parameters, no significant differences were observed in the results of comparing the proposed method with other methods. In any case, the more control there is over the network, the more control messages need to be exchanged, and our method is no exception.

According to Table 14, the network control overhead in the proposed method with an incoming traffic of 1 packet per second to 1 packet per 0.6 seconds increased up to 20 percent. This 20 percent difference in the control overhead in the proposed method compared to others is considerable (Figure 14) and the DDSLA-RPL was at

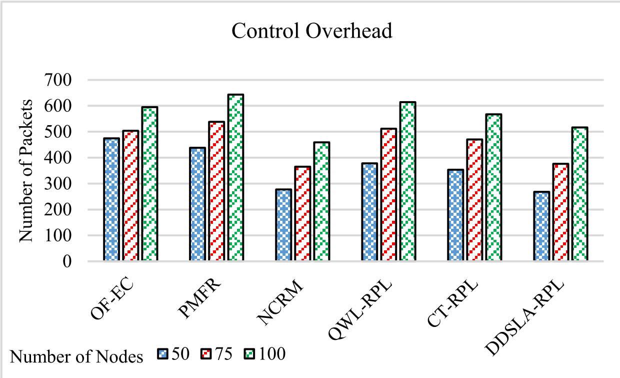



**FIGURE 14. Average number of network control messages during 20 test repetitions.**

**TABLE 14. Control overhead of the proposed DDSLA-RPL method at variable traffic rates.**

| Network Size in DDSLA-RPL | Packet inter-arrival time | | |
|---|---|---|---|
| | $\lambda = 0.6$ | $\lambda = 0.8$ | $\lambda = 1$ |
| 50 | 412 | 337 | 288 |
| 75 | 527 | 432 | 377 |
| 100 | 694 | 588 | 476 |

least 10 percent better than others in a traffic of 1 packet per second.

## V. CONCLUSION

Based on the results of this study, routing in the internet of things has many aspects to it, which due to its high dependency on hardware, software and embedded operating system and the environment it has created many diverse challenges. Items such as computational overhead, algorithmic complexities, security, reliability, hardware error tolerance, data error, and many other challenges will affect the routing and data transfer from source to destination. Therefore, our goal was to focus on the quality of routing services in the Internet of Things, especially the RPL method, and based on the effective parameters in providing quality of services, we have presented our idea with metrics of network structure and quality of routing services in a comprehensive method called DDSLA-RPL based on a multi-criteria decision-making system. In this method, creating and repairing a net-work graph is derived from the effective parameters in the formation and stability of links between nodes. For this purpose, the first objective function includes the proposed decision system based on step, link quality level, and signal-to-noise rate and energy consumption parameters for ETX, which has created a highly reliable graph. However, most of the innovation of the proposed method is summarized in the second objective function where a decision system with variable weight of parameters was proposed. Since in the real-world network environment the weight of the parameters is never equal in the first moment of the network and during operation, many researchers who have used fuzzy, K-MEANS, C-Means or similar methods in routing have not achieved the necessary accuracy and dynamism. Based on these reasons we equipped the weight of the parameters of our decision system with distributed learning automata. This automaton updates the weight of the parameters in the decision system based on the feedback it receives periodically from the environment and leads to increased lifespan of nodes and higher quality of network services. Our results indicate that the proposed method outperformed other similar methods in recommended tests such as average lifetime, energy fairness index, graph consistency, latency, forwarding and packet delivery rate in the network. For further re-search, we intend to use the DDSLA-RPL method in the underwater sensor network environment by changing the properties and network environment.

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