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A LOAD BALANCING ENERGY OPTIMIZATION SCHEME BASED ON DEEP LEARNING AND ABC ALGORITHM IN IOT

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ABSTRACT

The IPv6 Routing Protocol (RPL) for Low energy and Lossy Networks (LLN) become authorised by using the IETF as the standard routing protocol for IoT in March 2012. Since then it's been used for diverse IoT programs. This white paper addresses RPL troubles consisting of load imbalance that reason congestion on some nodes, severely degrading community overall performance, and lowering network electricity and lifespan. In this paper, we recommend a deep gaining knowledge of bee colony-based multiple recursive RPL (DBMRPL), a modification of RPL for IoT networks that makes use of a balancing model to keep away from congestion. This reduces network energy intake, extends network existence and decreases packet loss. DBMRPL is evaluated in two steps. First, a multi-hop go back objective characteristic based on bee colonies is supplied. Within the second step, we develop a singular discern selection mechanism that dynamically selects the quality figure via deep learning and dynamic metrics. The effects with a trendy rating of display that the set of rules can make higher decisions approximately the fine parent than making choices primarily based entirely on figure rank. Finally, the performance of the proposed algorithm is evaluated through a Cooja simulator. The proposed set of rules indicates considerable enhancements in packet transport and community durability, strength, and convergence.

Keywords: Load Balancing, Context-Aware, Routing Protocol, Internet Of Things, Deep Learning.

I. INTRODUCTION

Internet of things (IoT) has grow to be an appealing subject matter for researchers round the arena in current years. The LLN has numerous electricity-restricted nodes, normally border routers. In some instances, there are numerous border routers [4].A border router is also known as a gateway. If a node can't talk immediately with the border router, it uses other nodes as intermediate nodes to the border router. This process is dealt with through routing protocols inside the network. Consequently, routing protocols play an crucial role in forwarding data from nodes to IoT border routers [5]. On this regard, the IETF has standardized a routing protocol for IoT known as RPL [6]. RPL lets in users to define routing techniques in keeping with their network requirements and choices regarding metrics [7]. This opportunity is furnished by means of the concept of objective characteristic (OF). This is additionally one of the major focuses of this newsletter. OF defines how a Node's suitability is determined by means of different nodes to apply the node as a means to attain the desires of the community [8]. RPL issues are analyzed in this file and one of the most vital troubles is the lack of load balancing. As a end result, a few nodes grow to be congested, and the strength of nodes including And network performance and lifespan is significantly decreased. Strength is one of the confined assets of sensor networks. So that is one of the maximum essential troubles in IoT.

To resolve this problem, you want to manage the energy of IoT devices. Energy control facilitates make bigger the existence of those devices [9] .This document introduces the Bee Colony and Deep gaining knowledge of RPL (DBMRPL), a change of RPL For IoT networks that makes use of a balancing version to keep away from congestion. Recommend. This reduces network electricity consumption and packet loss price, and extends community existence.The objective function (OF) is a central concept in RPL. OF defines how metrics are combined into ranks in order for protocols to use rankings to build efficient routes. The RPL layout procedure does no longer keep in mind load balancing and congestion avoidance. The site visitors passing through a figure node and the scale of its subtree are not taken into consideration within the parent choice manner. This consequences in a unbalanced tree. Great research has been carried out on RPL load balancing, some of which is mentioned in the next phase. Unbalanced Tree algorithm: Tripathi proposed a greedy algorithm to solve the load balancing hassle. He calculated the load imbalance thing for each routing he degree. On this way, nodes Prone to congestion are identified. This set of rules involves very complex calculations. Consequently, it consumes numerous sources and time. TREEB Algorithm: Kulkarni proposed a method for load balancing. This way the DODAG root knows how many nodes each subtree has. A node that wants to join a DODAG knows the number of DODAG nodes and joins the DODAG with the lowest number of nodes [19]. This method does not affect the load balancing of each tree individually, it just tries to keep the trees the same size. For example, this method can perfectly generate The authors of [22] proposed minimum degree RPL (MD-RPL). It builds minimum degree over trees to allow load balancing of RPL. MD-RPL modifies the original tree formed by RPL to reduce its degrees. MD RPL improved the maximum power consumption, indicating a more robust network. Other studies relatedto minimizing energy consumption use different approaches, such as: This white paper focuses on the problem of load balancing and congestion, and his DAG method under traffic load and dynamic load. This white paper focuses on the problem of load balancing and congestion, and his DAG method under traffic load and dynamic load.The above problem and the objective function alone cannot solve the imbalance problem, only changes the location of congestion for each period, so it is a good choice for load balancing. Mechanisms to select parents And the reduction in energy consumption is presented in the second stage. Training can be incorporated into this approach as follows: Nodes dynamically learn which parent provides the best route according to load balancing and remaining energy and node buffers.

II. MATERIALS AND METHODS

2.1 Solution to the above problem

This document aims to present a modified version of his RPL for IoT networks. It uses a balancing model to prevent congestion, save network energy, and extend life. So the first step is to prioritize the parameters using test methods and available algorithms to present the best for the objective function. In the routing phase dynamic and variable factors are examined and tested and the parent selection mechanism selects the best one for the training algorithm.

Link Quality Indicator (LQI), Signal to Noise Ratio, Buffer Size, and Remaining Energy are the most effective. Then OF is applied according to the resulting factor using ABC and a 3-hop chain.

Running the ABC algorithm evaluates the parent nodes and introduces the best 5 parents for each node.

The last parent of each node is selected using dynamic routing factors such as buffer size and remaining node energy according to a deep learning algorithm.

The proposed method has been evaluated by universal simulation on the Cooja simulator and the result is , which is compared with the results of previous algorithms.

2.2. Description of Proposed Method

The Swarm-based optimization algorithm finds a solution by a joint trial-and-error method. Peer-to-Peer The learning behavior of social colonies is the main driving force behind the development of many efficient swarm-based optimization algorithms. The ABC optimization algorithm is a new addition to this category. Like other population-based optimization algorithms, ABC consists of a population of potential solutions.

Referring to ABC, a possible solution is a bee food source. Fitness is determined by the quality of the food source (amount of nectar). There are 3 types of bees in the colony: show bees, busy bees, scout bees.

The number of busy or show bees corresponds to the food source. Commercial bees are associated with food sources, while spectator bees remain in hives and are bees that use information collected by commercial bees to determine food sources. A busy bee who has run out of food sources, he becomes one scout Bee and randomly searches for new food sources Like other swarm-based algorithms, ABC is an iterative process. There are two basic processes that guide the evolution of ABC populations.

A variation process that allows different regions of the search space to be explored, and a selection process that ensures the use of previous experience. However, it has been shown that ABC may keep from approaching the global optimum even if the population has not converged to the local optimum (Karaboga and Akay 2009). The ABC process requires a cycle of four phases. Initialization Phase, Busy Bee Phase,Observer Bee Phase, Scout Bee Phase.

The focus was on implementing targeted functions specifically optimized for IoT networks. We used link quality indicator (LQI) and signal-to-noise ratio (SNR) as node routing factors in the optimal parent selection process of RPL and presented an approach for constructing nodes. DODAG structure.

2.2.1. Objective Function

After receiving DOIs from its neighbors, each non-root node computes the cost of the route through its neighbors. A proposed objective function to find a route from a source to a destination is used by parents with high forwarding (cross) probabilities. The transition probability from source I to destination d via parent j of node i is computed as

$$P_{ijd} = \frac{[\tau_{ijd}]^{\alpha}[LQI_{ijd}]^{\beta}[SNR_{ijd}]^{\delta}}{\sum_{i\epsilon N_i}[\tau_{ild}]^{\alpha}[LQI_{ild}]^{\beta}[SNR_{ild}]^{\delta}} \quad (1)$$

Quality index and signal-to-noise ratio (SNR) and all above zero (≥ 0)

(A) τijd is distance related.

(B) LQIijd is the heuristic value associated with LQI.

(C) SNRijd is a heuristic value related to SNR.

Also, Ni is a collection of i-parents, where l is the parent of i and provides a route to destination d. The DIO message gathers the transfer quality of each link and the SNR of each node while moving on the network. The content updates its factors (by computing its path to the parent) and starts to send its own DIOs after a node computes the route's cost for all its neighbours and selects the best parent with regards to the related ranking for the selected factor.

Finally, the child node orders its list for the available parents through the highest degree of probability and connects to the root node through the highest ij value.

2.2.2. Computing Relative Criteria

The link quality indicator (LQI) and the signal-to-noise ratio (SNR) are considered for calculating relative factors (criteria). The link quality indicator is the multi-hop average (path link quality is equal to the average link quality in all hops), whereas the signal-to-noise ratio is a concave function (the signal-to-noise ratio for one route is limited by the link that has access to the highest signal-to-noise ratio). The shortest path should minimize the growth factor from to, but a convex function is used to maximize the signal-to-noise ratio. To prolong the life of your network, it is recommended that you avoid choosing nodes with a low signal-to-noise ratio. Poor link and high noise Because choosing rate increases the packet loss rate in the network and wastes resources (energy and time). Reciprocal values were not used in the calculation of these parameters as the ratios of the above parameters are the same.

Link Quality Indicator

Link Quality Indicator (LQI) is the parent's current average LQI for DIO messages from the source to the destination, through the parent, while the DODAG structure is being built.

level LQI chain:

$$LQI_n = Max\{LQI_n , (LQI_{n-1} + LQI_{n-2} + LQI_{n-3} /3)*\Theta \} \quad (2)$$

The best Θ value was 0.20.

LQI was calculated using the following equation modeled after the actual hardware specification of the CC2430 Microchip.

$$LQI = (CORR - a) \cdot b \quad (3)$$

Signal-to-noise ratio

The model proposed by [37], [38] is used to approximate the signal-to-noise ratio. This model relies on simple, low-memory computations to match sensor nodes while preserving the accuracy of the original model. The model was implemented according to the following approximation: The maximum signal-to-noise ratio [39] between origin and destination is:

$$SNR_{ijd} = max\left\{\frac{Signal}{Noise_{(l)}}\right\}$$

$$\forall l \in route_j(i,d) \quad (4)$$

Triple jump SNR chain:

$$SNR_n = \text{Max}\{SNR_n, (SNR_{n-1} + SNR_{n-2} + SNR_{n-3}/3)*\Theta\} \quad (5)$$

The best Θ value was 0.20.

2.2.3. Queue Management and Congestion Control Using Deep Learning

The second phase approach of the proposed method focuses on the problem of queuing in RPL-implemented routing in IoT networks.The approach attempts to implement proactive mechanisms to prevent queue buffer overflows and manage future network traffic. Each parent node (not leaf) of the RPL mechanism has two important roles. Other children connected to themselves known as sinks. However, an important point about wireless networks is that there is no guarantee that the network will be covered. Parent change mechanism with deep learning

$$\mathcal{E}_n = \begin{cases} E_{init(n)} - E_{cur(n)} / E_{init(n)} & n = root \\ \text{Max}\,[(\mathcal{E}_{n-1} + \mathcal{E}_{n-2} + \mathcal{E}_{n-3})/3]*\Theta\,,\ E_{init(n)} - E_{cur(n)} / E_{init(n)} & n \neq root \end{cases} \quad 6$$

Facilitate fully connected feedforward structures between all possible entrances and exits will be Each layer of the deep net is and consists of a large number of neurons that are connected to neurons in neighboring layers but not connected to in the home layer. The output from each neuron is the weighted sum of all inputs. The proposed Deepnet-based Parent Change Mechanism (DBM-RPL) takes into account the priority weight of each input (queuing, energy metrics). These weights indicate the strength of the corresponding routing metric. DBM-RPL takes into account a sequence of inputs, outputs, network structures and mathematical steps.

The remaining multihop energy of the return node (Ɛ(n)) is proposed to approximate the remaining energy of the link between the recipient of the DIO message and her three link energies. des DODAG examines return parent nodes.

where n is the current node, unit(n) is the initial energy level, and Ecur(n) is the current energy level of node n. Einit(n) – Ecur(n) /Einit(n) is the remaining energy of node n. Ɛ(n) is the remaining energy state of the node chain in the root. That is, the energy balance of a node is taken into consideration in return, but the influence of the energy balance of the parent node decreases as the root gets lower. Θ was assumed to be 0.20. In our calculation method, the key factor in the proposed method is Ɛ (n), which distinguishes our ranking method from others. This factor gives multi-hop return information to the ranking formula. If the protocol does not take into account the previous parent's state, select a parent that has congestion problems on the route to the tribe, even if the selected parent is in good standing with respect to the tribe There is a possibility. It's a buffer with one performance left. Using multi-hop parent information, this paper shifted the focus from one parent condition to multi-hop chain condition of parents, resulting in a general view of the condition of a node for transformation to parent. Lead The next important metric for choosing an efficient parent is the proposed buffer:

The buffer size is calculated by the following formula: parent is obtained (via DIO message).

$$Q_n = \begin{cases} Q_n & n = root \\ \text{Max}\,[(Q_{n-1} + Q_{n-2} + Q_{n-3}/3) * \Theta], Q_n & n \neq root \end{cases} \quad 7$$

Then multiply the average of her three previous parents by Θ to reduce the influence of the previous parent. Then, θ is 0.20.

Below are the parameters for deep learning.

number of solutions = Ns

number of iterations = Ni

learning convergence = lc(0 to 1)

maximum number of nodes for each solution = Nmax

Ɛ(n) = parent chain energy

Q(n) = parent Chain Buffer. Evaluate the learning metric (LM).

$$LM_i=W_1 * \mathcal{E}(n)+W_{ni} * Q(n) \quad (8)$$

$$LC_{TH}=(\sum LM_i / N_S) \quad (9)$$

(b) Repeat step (a) above Ns times.

III. RESULTS AND DISCUSSION

Table 1 shows the grid simulation conditions proposed. According to Table 1, 180 sensor nodes were randomly distributed in the simulated environment and evaluated in these tests, and a basic method similar to the proposed yielded Dynamic routing is evaluated on how successful it is in terms of energy efficiency.

Table 1: Simulation conditions Provides a recursive model.

Value	Parameter
180 node	Number of nodes
240 m*240 m	Network environment
30 to 50 streams per minute	Network traffic rates
30 m	Node radio board
5 J	Primary energy of the node
CBR	Traffic type
200 s	Simulation time

Load balancing and congestion avoidance result in reduced network power consumption, longer network life, and reduced packet loss.

HECRPL [34] is a distributed, reliable and energy efficient routing protocol. HECRPL considers both lossy wireless link rate and power consumption to estimate routing costs. In HECRPL, routing decisions are made with the goal of minimizing power consumption. HECRPL selects the optimal Cluster Parent Set (CPS) by a top-down approach combined with transmit power level selection.

HEC RPL can significantly extend network life and provide much more robust network connectivity than the benchmark increase. However, due to the scheduled prioritization of CPS adjustments, we cannot take advantage of the spatial reuse feature. Also, resource constrained networks are prone to congestion. Efficient load balancing schemes are required to alleviate congestion problems. Another paper comparing the proposed methods, E-RPL [33], showed energy efficient routing in his IoT using ABC. The proposed E-RPL considers multiple routing factors and selects efficient parent nodes to build an optimal DODAG structure. To develop an optimal DODAG structure with reduced routing overhead, E-RPL introduces concentric corona based network partitioning to dynamically determine the value of broadcast count in terms of node density and coverage. Using ETX and rank values effectively balances routing performance and power consumption. However, different network sizes should be evaluated to demonstrate routing scalability.

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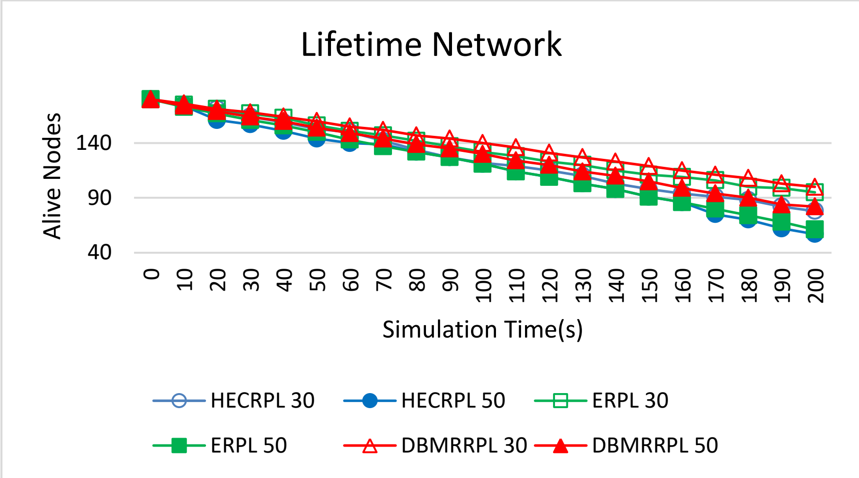

Figure 1: Network Lifetime

Generating a high quality link, knowledge-based parent selection and taking node energy parameters into account in the decision system's computations have reduced the probability of selecting a low energy node in the network in the proposed method; which delays the death of the network's first node.

3.1. Routing control overhead

Figure 2 shows the results of this test, in which the proposed DBMRPL algorithm was able to outperform the HECRPL and ERPL base methods due to considering the BEE colony algorithm and Deep Learning for generating the optimal route and involving node energy and queue parameters causing processing, queuing, and publishing delays as well as the upstream parent's accessibility.

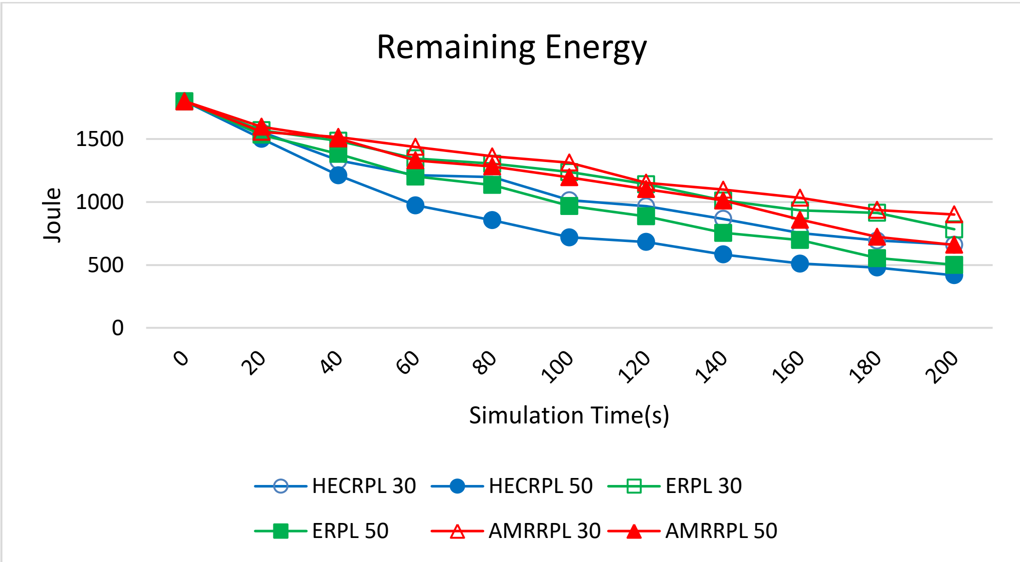

Figure 2: Remaining energy

Figure 2 has taken the average node energy consumption in the network's traffic ranges into consideration, which indicates the proposed DBMRPL method's awareness of network energy and condition. Overtime, simulating this process will reduce the proposed network's energy consumption.

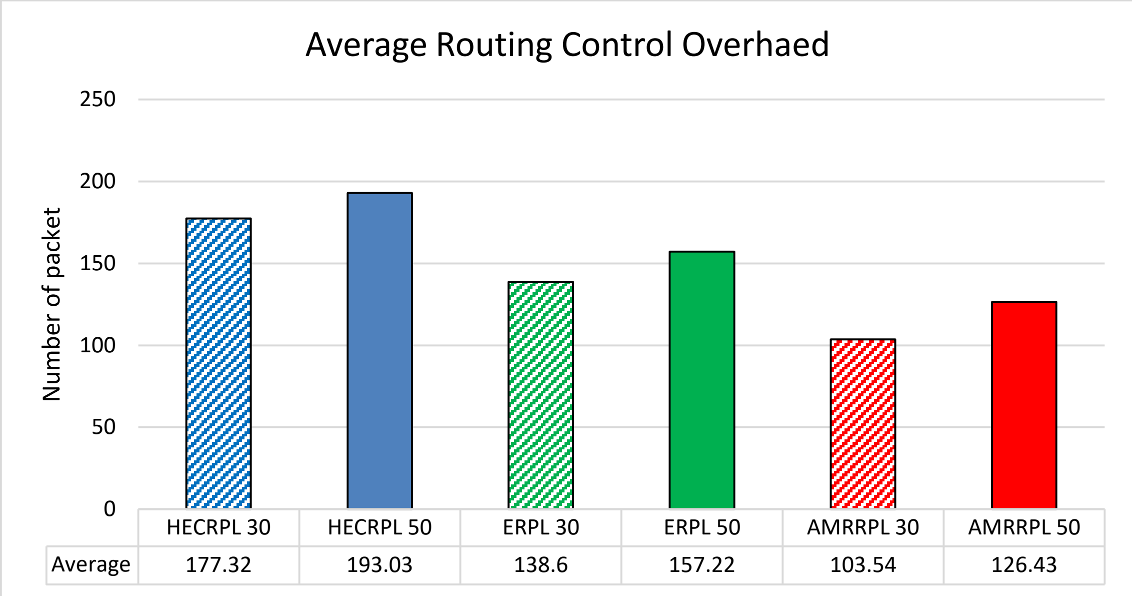

Figure 3: Routing control overhead

3.2. Delivery Rate Test

However, the main challenge of delivery rate in the RPL is in heavy traffics which can cause bottlenecks in the network and disturb its delivery rate. The results indicate that the DBMRPL method could yield a higher, acceptable delivery rate compared to the other two methods. Figure 4 shows the results of the packet delivery rate test.

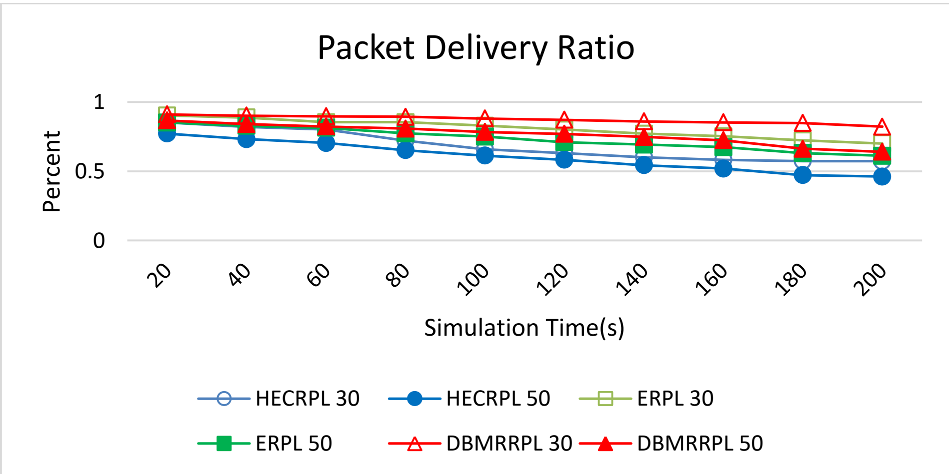

Figure 4: The results of packet delivery rate

IV. CONCLOSION

This paper proposed the the Deep learning-Bee colony based multiple recursive RPL , abbreviated to DBMRPL. As a result of load balancing and congestion prevention, it will reduce network energy consumption, prolong the network lifetime, and reduce packet loss. The proposed method was evaluated under different scenarios in Cooja, proving that the DBMRPL outperformed existing algorithms with regard to packet delivery, energy consumption rates, and network lifetime and stability through the load balancing model and congestion prevention.

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