Routing Protocols for IoT Applications based on Distributed Learning

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1. INTRODUCTION

Recently, there has been a high interest in the distributed computing in wireless networks, especially in the emerging pattern of Internet of Things (IoT) communications, where IoT instruments are supplied with independent processes, communication and storage capacities [1]. The important consequences include (i) a more economical approach with locally decreased data volume by in-network processing, (ii) just the processed outcomes are routed rather than all raw data, directed across a costly (multi-hop) wireless network. Therefore, bandwidth and energy are saved, the latency is decreased, and the network life is prolonged in an IoT network with restricted resources [2].

The IoT influences various application domains, including smart grids [3, 4], home automation [5], drone-based systems [6], healthcare systems [7], and industrial supervision [8, 9]. It is essential to use new wireless technologies to support innovative IoT applications and allowing large-scale connectivity among IoT policies. However, the combination of the IoT ecosystem and current wireless networks results in many issues, including self-organizing operation, coincidence with human-kind systems, and limited communication sources [7, 10]. Besides, the IoT devices are often machine-type ones, which have a significant difference from conventional human-type tools, such as smartphones based on performance needs, memory, computation, traffic patterns, and energy constraints [11]. Additionally, the IoT tools require short packets, ultrareliable transmissions, and low latency. Thus, re-planning of the current wireless networks is required for solving these IoT challenges.

A distributed learning approach with the Low Power Networks (RPL) protocol (CCR-based RPL protocol) was presented by Azari and Cavdar [12] to solve this problem to collect data in multi-hop IoT networks effectively as represented in Figure 1. Appropriate allocation of restricted resources is achieved using the

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**ABSTRACT**

The IPv6 routing protocol for lossy and low power networks (RPL) was introduced in March 2012 by the Internet Engineering Task Force (IETF) as the standard routing protocol for the Internet of Things (IoT). Since that time, it has has various applications in IoT. Despite meeting the IoT network necessities by RPL, some unanswered issues have not been devised primarily for IoT usages. However, gathering a large amount of data from these networks with videos and images typically leads to traffic congestion in the network’s central part. For providing a solution for this issue, the content-centric routing (CCR)-based RPL is proposed in the present study, where the content specifies the routing pathways. It is possible to attain a larger data aggregation ratio by routing the relevant data to the middle relaying nodes for the process. Thus, effective traffic is generated in the network. Subsequently, latency is significantly reduced. Moreover, energy use is decreased on wireless communication. More integration was conducted between IETF RPL protocol and CCR, using the MATLAB platform. Finally, according to simulated and implemented results, the CCR-based RPL behavior based on the high packet transfer rates is improved, and the numbers of dead nodes are reduced. High energy efficiency and low delay rates are obtained in communication using the proposed routing method.

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distributed method concerning the IoT tools’ Quality of Service (QoS) needs [13]. These tools should have the capability to separately obtain their communication resources as supposing their regular communication with the root node is not practical, given their severe resource constraints. Moreover, the root in a massive IoT cannot manage the communication resources in all tools promptly. Thus, the distribution of resources is essential for all assignment occasions in the IoTs, considering the limited capacities of the IoT tools in terms of computation and memory. Deployment of the IoT over the available networks with limited communication resources would be confined by a resource assignment framework that meets the pre-described requirements.

The current research focuses on two critical dimensions of IoT networks: energy efficiency and transfer rates in a network having a high and heavy dynamic load [14]. A new objective functions (OF) is presented in this study, which periodically investigates the last states of node chains in the pathway to the root while avoiding the passage of additional message requests in the network. Additionally, this work provides a new routing metric to respond to the network’s dynamicity requirement. Besides, a new approach is presented to parent selection.

2. REVIEW OF LITERATURE

Various research works have been conducted on the adaptive routings in objective functions and IoT, including energy-consumption, load balancing, and time delay. However, there are a rare number of studies conducted on distributed learning in routing. Some studies related to context information-based routing are presented in this section.

Mohamed et al. [5] studied the proactive routing protocols with the highest energy efficiency for a homogeneous system. The Wireless Sensor Network (WSN) energy efficiency results from three fundamental necessities: network overhead within network arrangement and re-arrangement, selecting a route for data transmission, and fault tolerance or network adaptability. For guaranteeing a longer network lifetime, it is required to have a changeable network, the overhead must be confined to a minimum rate, and multi-hop routing must be used. Thus, selecting the energy-efficient routing protocols must be done cautiously based on application necessities and system requirements. This work attempts to deal with the network lifetime analysis for the reactive routing protocols in heterogeneous and homogeneous systems.

Aman et al. [15] investigated the RPL acceptance in the Cooja simulator by comparing the real networks’ findings. They showed higher energy consumption by both the sink and client nodes in a real network compared to the Cooja simulation calculation. The packet delivery rate (PDR) was found to be lower in actual scenarios and is considerably decreased by the network distance and size. However, interference is not involved from external wireless, signal reflection, and asymmetric links. This model is yet extensively employed in different works.

A new uplink bandwidth assignment algorithm was presented by Mardani et al. [9] for highly dense 4G networks of the human-to-human (H2H)/ machine-to-machine (M2M) services in a co-existing setting. The algorithm utilized interval type-2 fuzzy logic for dealing with system ambiguities. The intelligent type-2 fuzzy algorithm specifies the optimum bandwidth ratio for every M2M/H2H service flow. To determine the correct bandwidth ratio for every type of flow, the solution used the M2M/H2H necessities, including the Human Type Communication (HTC) output, the power level of Machine Type Communications (MTC) tools for non-real-time services, and the highest potential for real-time services. Assessment of the suggested system performance was done based on throughput, bandwidth utilization, and delay.

A context awareness framework known as Awareness Cognition (AC) was proposed by Kim and Yoon [16] that focused on the Ambient Intelligence (AmI) system’s middleware layer. Using this framework, the prediction problem was solved by integrating multiple contexts for detecting personalized knowledge. Additionally, utilizing knowledge-based cognition approaches for discovering future changes, a fusion contextual learning model was generated for behavioral knowledge detection. Besides, modeling was provided for collecting data from various sensors in the AmI system in a single meaningful context [13, 17].

Two algorithms with two constraints were presented by Huang et al. [18] for challenging the multicast routing problem for multimedia communication in the IoT. Multiple constraints are integrated into a complete metric using the entropy method. Thus, the proposed algorithms significantly decreased the complication of multi-constrained multicast routing problems, and some popular algorithms can be applied for problem-solving. Additionally, the theoretical analysis was suggested on the approximation and complexity of the suggested
algorithms, and wide simulations were carried out to assess the algorithm's performance. According to analytical and experimental findings, one of the proposed algorithms is better than a representative multi-constrained multicast routing algorithm in terms of speed and accuracy. The results provide an in-depth perception of the multicast routing algorithm design for multimedia communications in IoT.

Rani et al. [19] proposed an improved solution for organizing objects to implement an energy-efficient and scalable IoT. Firstly, the framework was presented to deploy the IoT with scalability features providing higher extensibility. Afterward, considering the framework, an optimization outline can support the deployment of an IoT with energy efficiency. This optimization outline is confined by the loads on wireless links and energy expenses. Compared to conventional WSN outlines in terms of network lifetime, time, and scalability, various numerical tests confirm superiority of the proposed outline. This work addresses the challenges of the way of using heterogeneity advantages. Nevertheless, improvement of end-to-end delay, throughput parameters, packet delivery ratios, and data compression approaches are proposed to achieve more effective green IoT.

An effective self-organization protocol called ETSP was presented by Qui et al. [20] for sensor networks of IoTs, saving energy and allowing a prolonged lifetime for a network by restricting a tree-based network. The nodes’ weight, such as hop, residual energy, distance within the nodes, and a number of child nodes were used to determine whether it can be a sink node. Therefore, the depth of the tree is improved by ETSP. The topology of the network is drastically changed over the data transmission procedure. Because the sink nodes consume energy faster than other nodes, each sink node is dynamically re-chosen. The simulation results showed that with ETSP, reliable tree-based networks could be generated, the energy consumption can be reduced, and the sensor network’s lifetime can be extended.

Shen et al. [21] presented an energy-efficient centroid-based routing protocol (EECRP) for controlling the WSN-assisted IoT energy. To this end, they solved the forming clusters problem considering the distance to the energy centroid. An enhancement algorithm was presented in the present study regarding the number of cluster head nodes and the number of dead nodes. The simulation results indicated that with the base station (BS) deployment in the network, it would be possible to transfer a great amount of data by the EECRP with very low energy dissipation. Besides, the EECRP has a longer network lifetime than the GEEC, LEACH-C, and LEACH. This protocol will be enhanced for future study by identifying the multi-hop pathway from cluster head (CH) nodes to BS. For transferring data packets, a multi-hop pathway is used by the CH nodes. It is hoped that the future protocols have good performance for the BS outside the network.

3. STATEMENT OF THE PROBLEM

RPL, which is primarily devised for low-power lossy networks, possesses numerous notable characteristics, including self-healing mechanism, loop-freeness, low-battery use, and fast topology construction. Nevertheless, it fails to address issues of a network with a high traffic rate as it was chiefly devised for low traffic networks. When there is a high network traffic, RPL cannot control it well, making various difficulties for the network, such as energy depletion, load imbalance, and high packet loss rate. It would be more troublesome when a depleted node is the only intermediate node for a network section close to the root. RPL problems are classified under heavy and highly dynamic loads as follows:

1. With the computation of the rank through two OFs including Objective Function Zero (OF0) and minimum rank with hysteresis objective function (MRHOF) in normal RPL, many studies have been conducted for changing the RPL objective functions based on related research works. Nevertheless, as it is known, the former parents of a node in the sequence are not considered by the ordinary RPL OFs and other proposed OFs. A node could seem proper for serving as a parent; however, the node parent or another parent in a parent sequence could have low remaining power or small buffer space, which causes inappropriate selection of the parent in the network with high traffic.

2. The route is created concerning the rank. When attempting to connect the network or alter its parent by a node, the network is selected with a lower rank value. Nevertheless, the parents’ rank is obtained in the primary phases of connecting the network. Various difficulties could appear in the pathway to the route followed by the rank computation. Thus, the rank value in a high traffic dynamic network cannot completely represent the last and real mode of the candidate parents.

4. METHODOLOGY

As a node connects to a Destination Oriented Directed Acyclic Graph (DODAG) and if a DODAG Information Object (DIO) message is received by it, the node can process it via the following ways:

1. Removing the DIO package for some RPL criteria.
2. Processing the message for keeping its location in the network.
3. Improving its location by gaining a lower rank in DODAG.
When a node's rank decreases, the node must eliminate all parents with a rank lower than its new rank from its parents' list. Thus, the development of a loop in the network is prevented. Following this phase, the nodes each has a default route to the root and they would be able to send their data packages to the root.

According to the simulation results, the efficiency of the CCR-based RPL routing approach in data aggregation and recognition in IoT network is high. In this section, using the content-based RPL approach in the direction of data aggregation rate, we compare the number of live nodes, energy consumption, the network balance, and correct data transfers with those in the conventional RPL approach.

Similar to the properties given in Table 1, the simulation's completion and the node routings in the network can be observed.

For increasing the routing efficiency in IoT network, we presented a content-based system in this work. In the presented system, each node utilizes the root-inquiry packages for recognizing the parent nodes to become aware of the number of packages arriving in the root. Utilizing this awareness, the level of confidence is calculated for the route that the parent provides. In cases of malignancy of the parent and when the level of confidence for parent node calculation is lower, the respective node chooses a parent with a higher confidence level among the candidate parents. Using this method, each node can efficiently prevent malicious nodes. It is possible to gain a higher data collection ratio by routing the intermediate relay node data in the processing order. Thus, it is effective in the reduction of the network traffic rate. Consequently, the delay in the data transfer can be significantly reduced. Moreover, we can annihilate data transfers following data collection, resulting in a decrease in energy consumption in wireless communications and saving battery energy consumption.

Three major units are included in this method:

1) Data collection unit: It gains information about the number of data packages arriving at the root by periodically sending the root-inquiry packages.

2) Confidence level calculation unit: This unit uses the information presented by the data collection unit and computes the confidence level of the route presented by the parent using the following equation:

\[ T(p) = 1 - \frac{P_{k\text{sent}_{ij}} - P_{k\text{delivered}_{ij}}}{P_{k\text{sent}_{ij}}} \]

if \( P_{k\text{received}} = P_{k\text{delivered}} \)

\[ T(c) = T(c) - 0.01 \quad \text{else} \]

where \( T(p) \): Confidence level of each parent (neighbors), \( P_{k\text{sent}_{ij}} \): Total number of packets sent to the root by specific node, \( P_{k\text{delivered}_{ij}} \): Total number of packets arrived to the root through each parent (neighbors).

3) Parent selection unit: It chooses a parent with a higher level of confidence among the candidate parents as the selected parent.

### 5. EVALUATION

To assess the protocol proposed in our work, the CCR-based RPL was simulated using the MATLAB simulator, commonly used for IoT. Then, the CCR-RPL was compared with conventional RPL. MRHOF was adjusted as OF of ordinary RPL, and the protocol factors were tuned based on the CCR-based RPL factors (Table 1). There are 800 nodes in our setting with 20 BS, which were established in 50m × 50m. The BS serves as the root, and the transmission range is 25m.

In this setting, duty cycling was disabled for reaching a high load in the network, and the first-in-first-out (FIFO) line was utilized with a volume of 80 packets. The simulation setting and the simulation parameters are represented in Figure 2 and Table 1. Besides, various traffic rates and nodes are considered for assessing the protocol proposed in our work under different conditions.

![Figure 2. Routing the network topology](image-url)
Firstly, a comparison was conducted based on the queue loss ratio. Figure 3 indicates two protocols with varying traffic loads (rising). According to the results, the numbers of the live nodes are increased by the network’s CCR-based RPL. Nevertheless, the other important property shown in Figure 3 indicates the worst case of the queue loss ratio in the nodes in varying traffic loads. We interpret it as the CCR-based RPL capability to make a more uniform DODAG concerning the network load.

Following application of the simulation, the following results were obtained:

Figures 3-8 indicate the higher proficiency of the CCR-RPL approach than the ordinary RPL in increasing system efficiency and reducing energy consumption. Thus, it reduces the number of dead nodes and energy consumption in the system and increases the system efficiency and power.

Figure 3. Comparing the number of the live nodes

Figure 4. Comparing the rates of transferred packages

Figure 5. Comparing the rates of the remaining energy

Figure 6. Comparing the balances dominating the system

Figure 7. The delay rates in package transfers
6. CONCLUSION

RPL routing protocol problems with heavy and dynamic load were addressed in the present work, focusing on the network lifetime and energy. It was observed that an ordinary RPL could not provide effective control over the heavy and dynamic loads. To provide a solution for this challenge, a load balancing and context-aware protocol was proposed considering the parent-chain rank before selecting the chain’s ultimate parent as the node’s chosen to parent. Thus, the load was tried to be balanced in the network. The present study took into account the residual queue and energy level of the candidate parents.

Additionally, a proper parent's rush was prevented, making instability problems and a high control message rate for the network. Our proposed protocol was assessed in MATLAB in varying conditions. It was proved that the performance of CCR-RPL is significantly better than RPL, while it does not impress a high overload for the network.

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