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Research Article

Fuzzy based Congestion Control and Congestion Aware Routing Technique for IoT Networks

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ABSTRACT

Introduction: In Internet of Things (IoT) networks, the existing congestion control mechanisms did not often scale efficiently or maintain the heterogeneity of devices, causing performance bottlenecks and uneven network performance. Existing congestion control protocols may not adjust well to these dynamics, causing increased packet loss, suboptimal performance, and higher latency.

Objectives: The main objectives of this work are to detect congestion at node level or link level and to determine congestion aware routing paths.

Methods: A Fuzzy-based congestion control and congestion aware routing (FCC-CAR) technique for IoT networks is proposed. In this technique, Q-learning is applied at each node to select the parent node based on the link quality, node degree and hop distance metrics. Then, congestion at any intermediate node is detected by means of congestion degree, packet processing delay and packet loss, by applying Fuzzy logic decision model. Depending on the detected congestion status, appropriate congestion control mechanisms are applied.

Results: Experimental results have shown that FCC-CAR technique minimizes the packet drop and delay while increasing the throughput.

Conclusion: Thus the proposed technique performs congestion control by means of congestion detection and congestion aware routing.

Keywords: Internet of Things (IoT), Congestion Aware Routing, Congestion Control, Q-learning, Fuzzy Logic

INTRODUCTION

IoT is defined as a system of uniquely recognizable, interoperable connected objects using Radio-Frequency Identification (RFID) technology. IoT indicates a wireless network of devices that communicate and share information with others through the Internet. IoT has become a vital element of modern technological development and is anticipated to experience significant growth in the coming years [1]. IoT technologies are now incorporated into a wide range of applications, including smart homes, smart factories, smart cars, smart security systems, cloud technologies, remote healthcare, and numerous other platforms across several industries [2][3].

Transmitting data efficiently from Internet-constrained IoT devices utilizing traditional network architectures, protocols, and communication technologies is mainly challenging for these resource-limited devices [4][5]. Managing congestion is a major problem in regulating traffic within cyberspace. Since the number of connected nodes grows, various challenges emerge, including energy conservation, scalability, reliability, security vulnerabilities, network routing, and network congestion [6].

If the packets are transmitted from the source to the destination, network congestion can cause packet loss or packet drops, in which many packets did not reach their anticipated destination because of excessive network load [7]. Consequently, routing protocols play a significant role in preventing congestion by efficiently distributing packets across multiple network paths. Implementing suitable methods for control congestion is crucial to maintain high throughput [8]. Since IoT is expected to be an essential part of the upcoming Internet, resource sharing could become a significant problem to its development if network congestion issues are not addressed. This congestion, in turn, reduces QoS and network performance [9][10]. Existing congestion control mechanisms did not often scale efficiently or maintain the heterogeneity of devices, causing performance bottlenecks and uneven network performance. They may cause increased packet loss, suboptimal performance, and higher latency.

The main objectives of this work are:

- To detect congestion at node level or link level
- To perform congestion control after congestion detection
- To determine congestion aware routing paths

In order to achieve these objectives, a congestion-aware routing and fuzzy-based congestion control technique has been proposed.

RELATED WORKS

Parween [10] introduced bottleneck bandwidth and round-trip propagation time new enhancement (BBR-NEnh), which is an Enhanced Congestion Control (CC) mechanism. In a 5G IoT heterogeneous network, it is designed for cross-layer congestion control. Khalek et al. [11] analyse the lwIP congestion control mechanism and emphasize its limitations. A set of novel algorithms designed is proposed to meet the unique demands of IoT—highlighting lightweight operations—while also ensuring scalability in terms of network size and performance. Buenrostro-Mariscal et al. [12] presented a cross-layer priority-based congestion control protocol (QCCP), which is achieved by the MAC and transport layers of communication devices. It's contribution is its approach to estimate and resolve wireless channel congestion without producing control packets, operating in a distributed way with a one-bit overhead.

PROPOSED METHODOLOGY

This work proposes a FCC-CAR technique IoT networks. In this technique, Q-learning is applied at each node to select the forwarding node depending on the dynamic network circumstances. Every node manages a combined routing cost for its neighbours, in terms of the link-quality, node degree and the hop-distance. Then congestion aware routing paths are established based on this routing cost metric. Congestion at any intermediate node is detected by means of congestion degree, packet processing delay and packet loss, by applying Fuzzy logic. Depending on the detected congestion status, appropriate congestion control mechanisms are applied.

Routing Path Establishment

Q-learning is deployed at each node to select the forwarding node based on the dynamic network conditions. It is a Reinforcement Learning (RL) method in which the agents are trained to select the optimal action using a Q-table (routing table) for each node. The action includes choosing the preferred parent node. The objective of the learning process is to recognize a congestion-aware routing path. The node selects a parent that provides the lowest node degree, best link quality, and shortest hop distance.

For this, each node maintains a combined routing cost (RC) for its neighbours, derived from link-quality (LQ), node degree and the hop-distance. Calculating the LQ at each node aids in balancing the load among nodes. It can be assessed in terms of Expected Transmission Count (ETX) metric and interference rate (IR). The ETX measurement between node m and n is denoted by ETX(m,n). In RPL standard, ETX(m, n) is periodically exchanged. It is estimated by

Hence LQ can be computed as

$$LQ(m,n) = ETX(m,n) + IR(m,n) \quad (1)$$

The node degree (ND_n) represents the number of neighbours of node n. The hop-distance (HD_n) represents the node n's hop-count towards the DODAG root.

Q-values are updated periodically through:

$$QV_m^{new}(n) = QV_m^{old}(n) + \beta[RC(n) - QV_m^{old}(n)] \quad (2)$$

Where $QV_m^{new}(n)$ and $QV_m^{old}(n)$ indicate the Q-values for the present and preceding intervals, respectively. β is the learning rate.

Then the routing cost RC can be computed as

$$RC(n) = \lambda_1 \, LQ(m,n) - (\lambda_2 ND_n + \lambda_3 HD_n) \quad (3)$$

where, λ_1, λ_2 and λ_3 are the weighting parameters of LQ, ND and HD.

It suggests that neighbours with minimum Q-values will be chosen with reduced probabilities and the neighbour with a higher Q-value will be the one chosen as a preferred parent. Then congestion aware routing paths are established based on this routing cost metric.

Fuzzy based Congestion Detection Mechanism

Congestion at any intermediate node is detected by means of congestion degree, packet processing delay and packet loss, by applying Fuzzy Logic Decision (FLD) model.

Congestion Degree (CD): It is estimated by comparing the number of packets sent to the wireless channel (Pk_{tx}) and the packets obtained by the node (Pkrx).

$$CD = \frac{Pk_{rx}}{Pk_{tx}} \quad (4)$$

Packet Processing Delay (PD): It is measured as the average time taken from the time of packet arrival (t_{arr}) until the time of transmission from the MAC layer to the channel (t_{tx}).

$$PD = t_{tx} - t_{arr} \quad (5)$$

Packet Loss: It represents the average percentage of packets lost at the MAC layer due to channel circumstances that are either busy or poor.

$$PL = \frac{PL_{ch}}{Pk_{rx}MAC} \quad (6)$$

Where PL_{ch} is the packet loss due to bad or busy channel conditions and $Pk_{rx}MAC$ is the number of packets received in the MAC layer.

Fuzzification: This includes fuzzification of input variables like CD, PD and PL. Suitable fuzzy sets are assigned a degree to these inputs. The sharp inputs consist of a mix of PD, PL, and CD. We consider three scenarios for CD, PD, and PL: high, medium, and low. The output variable CS represents the detected congestion status which has four possibilities: very high, high, medium and low.

Table 1 shows PD, CD, and PL as inputs, and the output indicates the congestion state that needs to be adaptively adjusted. Table 1 presents the combinations that are utilized to define the fuzzy sets.

S.No	Congestion Degree (CD)	Packet Processing Delay (PD)	Packet Loss (PL)	Congestion Status (CS)
1	Low	Low	Low	Low
2	Low	Low	High	Medium
3	Low	High	Low	Low
4	Low	High	High	High
5	High	Low	Low	Medium
6	High	Low	High	High
7	High	High	Low	High
8	High	High	High	Very High
9	Low	Medium	Medium	Medium
10	Low	Low	Medium	Low
11	Low	High	Medium	Medium
12	Low	Medium	High	Medium
13	Low	Medium	Low	Low
14	Medium	Low	Low	Low

S.No	Congestion Degree (CD)	Packet Processing Delay (PD)	Packet Loss (PL)	Congestion Status (CS)
15	Medium	Medium	Low	Medium
16	Medium	Low	Medium	Medium
17	Medium	High	High	High
18	Medium	High	Low	Medium
19	Medium	Medium	Medium	Medium
20	Medium	High	Medium	Medium

Table 1 FLD Rules

The designed fuzzy inference system is demonstrated in Table 1. This shows how the inference engine works and how each rule's output is integrated to obtain the fuzzy decision.

Defuzzification: It is the procedure of taking a crisp value out of a fuzzy set and utilizing it as a representation value. The centroid of the area scheme is considered for defuzzification.

EXPERIMENTAL RESULTS

The proposed FCC-CAR technique is simulated in NS2 and is compared with QCCP [12] and the traditional Minimum Rank with Hysteresis Objective Function (MRHOF) [13] protocol with respect to delay, packet delivery ratio and packet drop metrics. The number of nodes has been varied from 20 to 100 in a region of 1500mx300m . The number of exponential traffic flows has been varied from 2 to 10.

Results

By varying the number of nodes from 20 to 100, the performance of three algorithms is assessed.

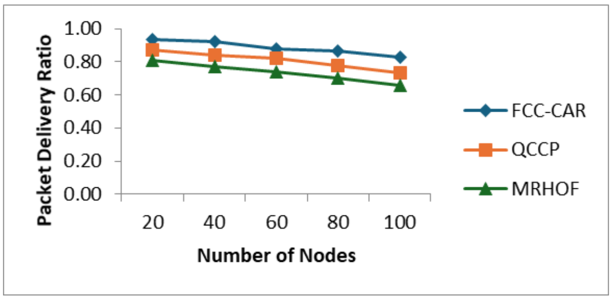

Figure 1 Packet delivery ratio for Nodes

The results of packet delivery ratio for different nodes are shown in Figure 1. It can be observed that the packet delivery ratio of FCC-CAR technique is 8% higher than QCCP and 16% higher than MRHOF.

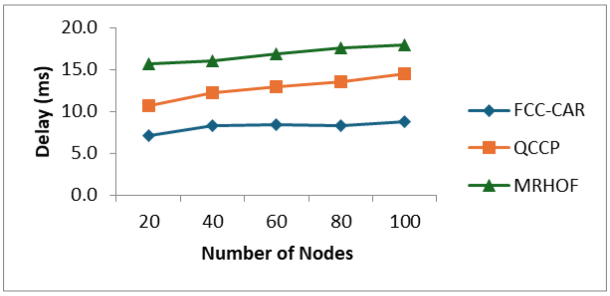

Figure 2 Delay for Nodes

The results of delay for different nodes are shown in Figure 2. It can be observed that the delay of FCC-CAR technique is 35% lesser than QCCP and 51% lesser than MRHOF.

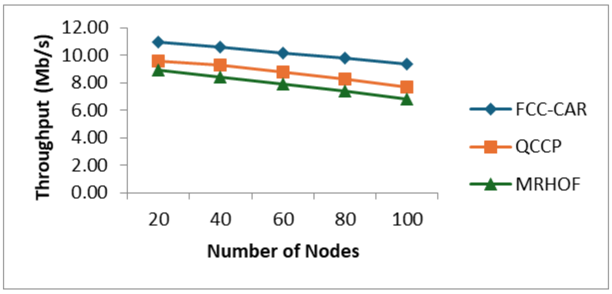

Figure 3 Throughput for Nodes

The results of throughput for different nodes are shown in Figure 3. It can be observed that the throughput of FCC-CAR technique is 14% higher than QCCP and 22% higher than MRHOF.

(ii) Varying the Traffic Rate

By changing the traffic rate from 10Kbps to 50Kbps, the performance of three algorithms is assessed.

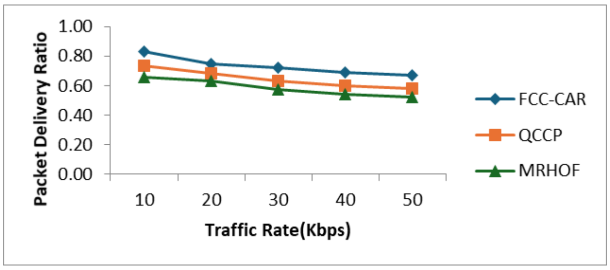

Figure 4 Packet delivery ratio for Rate

The results of packet delivery ratio for different rates shown in Figure 4. It can be observed that the packet delivery ratio of FCC-CAR technique is 12% higher than QCCP and 20% higher than MRHOF.

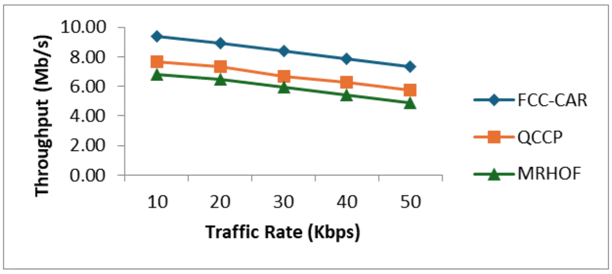

Figure 5 Throughput for Flows

The results of throughput for different rates are shown in Figure 5. It can be observed that the throughput of FCC-CAR technique is 19% higher than QCCP and 29% higher than MRHOF.

CONCLUSION

In this paper, a FCC-CAR technique is designed for IoT networks. Q-learning is applied at each node to select the parent based on the dynamic network conditions. Congestion at any intermediate node is detected by means of congestion degree, packet processing delay and packet loss, by applying FLD model. Depending on the detected congestion status, appropriate congestion control mechanisms are applied. The proposed FCC-CAR technique is implemented in NS2 and compared with QCCP and the traditional MRHOF protocol. Simulation results demonstrate that the FCC-CAR technique decreases the packet drop and delay while increasing the throughput, when compared to QCCP and MRHOF protocols.

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