Federated Learning Framework for Intelligent IoT Networks

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Abstract

The use of Internet of Things (IoT) devices has increased significantly due to their diverse application areas. The IoT sensors are normally deployed in a complicated environment. Maintaining these tiny devices is challenging and often incurs high system costs. These devices are expected to handle data processing and communication tasks independently. For network layer communication, a reinforcement learning mechanism is utilized to generate routing table entries intelligently. The Q-values in RL algorithm may have error variance in nodes having similar environmental conditions. Thus, federated reinforcement learning (FRL) is proposed to represents the fair estimation of Q-value. The proposed FRL mechanism enhances the communication capabilities of IoT networks. The performance evaluation of the proposed mechanism is provided through Contiki 3.0 Cooja simulation.

I. Introduction

Internet of Things (IoT) is a network of smart devices communicating with each other in a lossy environment. These low-power and lossy network (LLN) devices are battery-powered and contain limited computational and storage capabilities. Therefore, the communication functions of these devices are supported by lightweight low-power consuming protocols. For example, the network layer uses an IPv6-based routing protocol for low-power and lossy networks (RPL). Similarly, the MAC layer is based on a simple back-off mechanism to avoid collision [1]. The communication mechanism of these devices can be optimized with the help of machine learning (ML) based techniques such as reinforcement learning (RL). In RL, an agent interacts with the environment, observes the reward, and learns the optimal policy, for example, Q-learning mechanism. In RL, building policies is a computationally expensive process [2]. To optimize LLN devices, we can utilize the federated RL (FRL) technique that allows numerous LLN devices to construct a strong ML model. In FRL, an agent shares its learning model with its neighboring nodes having similar environmental conditions. The neighboring devices perform their learning algorithm upon reception of the learning model from the agent. In this way, decentralized FRL enhances the network performance efficiently. In this paper, FRL framework is devised for intelligent IoT network communication.

Ⅱ. Proposed Mechanism

The FRL-empowered mechanism is introduced for LLNs optimization. A learning agent iteratively observes the environment and collects the collision information from medium access control (MAC) layer. The learning agent uses collision information from the MAC layer to generate routing table entries at the network layer. The network layer is based on routing protocol for low-power and lossy networks (RPL). The routes are maintained as a graph, referred to as the destination-oriented directed acyclic graph (DODAG) [3]. The DODAG is based on parent-child topology where each node is ranked based on its position in the network graph. A child node selects a suitable parent node for path forwarding from the list of potential parent nodes. Each parent node can have multiple child nodes and each child node selects a parent node from the list of potential parents. This parent selection action yields either a positive or negative reward in terms of a channel collision. The child nodes are ranked based on RPL protocol ranking formulation using collision information as an objective function metric.

In the proposed scheme, FRL scheme works in three phases. Firstly, the child nodes share their rank values with the neighboring nodes using DODAG information object (DIO) control packet. The nodes having similar rank form a learning group and select one of the nodes in a group as a learning server node. The child nodes obtain the first value function such as (Q-learning in a typical RL model) from the server node. Then in the second phase, each child node in a group also obtain their value function using their own local data known as the local model. Then each node sends its local model to the server node. The server node averages these local model values obtained from other nodes. In the third phase, the server node applies this average value to obtain its next value function. The learning agent updates the learning model using a local learned model from other child nodes having the same wireless environment. The value function that server node measure is known as the global learning model

In this way, child nodes computing the forwarding path can learn the wireless environment faster using a global learning model from the learning agent. The child nodes assume a learning agent as global learning of wireless environment. The neighboring nodes around the learning agent update their local learning using the learning agent learned model. Individual learned Q-values may suffer from an overestimation of collision information. Each node integrates its learned Q-values in the DIO packet to collaborate with the learning agent. This federated Q-value provides a second Q-value function for the learning agent. The global learned values in the learning agent represent

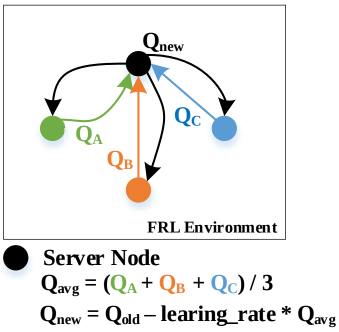

Fig. 1 FRL environment for the proposed mechanism.

the fair estimation of the Q-value. In other words, both the local learned values and global learned values are obtained from the same set of experiences in same environment. In this way, the learned Q-values have a lower chance of error variance. The process of FRL mechanism for the proposed technique is illustrated in Fig. 1.

Ⅲ. Results Analysis

We utilized Contiki OS Cooja simulator for our proposed mechanism evaluation [4]. The simulation is performed on a network size of 20-50 nodes. These nodes are placed randomly and generate random traffic patterns. The nodes are based on the Zolertia Z1 mote platform. The proposed scheme is compared with the minimum rank with hysteresis objective function (MRHOF) and objective function zero (OF0). We used Python 3.7 to analyze the raw data from the simulator.

Fig. 2 shows the packets reception ratio (PRR), using standardized protocols (OF0 and MRHOF) compared to the proposed protocol. The MRHOF and proposed protocol develop a more reliable network compared to OF0. Since OF0 is only based on hop count and has no link reliability mechanism. The MRHOF uses a continuous probing mechanism to measure link quality, and thus the performance is slightly less compared to the proposed mechanism.

The frequency of the control packets depends on network stability. When the network is stable, fewer packets are transmitted and vice versa. The description of control packets in the network is depicted in Fig. 3. The percentage of overheads is highest in OF0 due to low PRR. When a packet is dropped due to collision or congestion. The node retransmits it until the maximum MAC layer limit of eight attempts. Thus, more packets are transmitted to update the routing table entries. In MRHOF, the control packets are higher due to link quality estimation calculations. The proposed method shows a significant improvement in reducing the overall control packets.

Ⅳ. Conclusion

In this paper, we proposed a federated learning framework to enhance IoT network learning estimation. We define the MAC layer collision

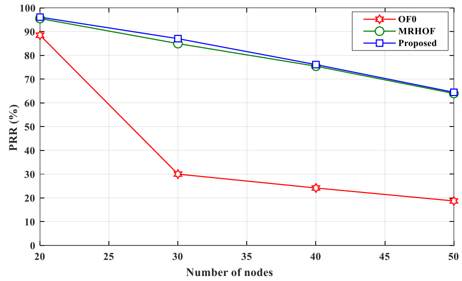

Fig. 2 Packet reception ratio (PRR) in different network sizes

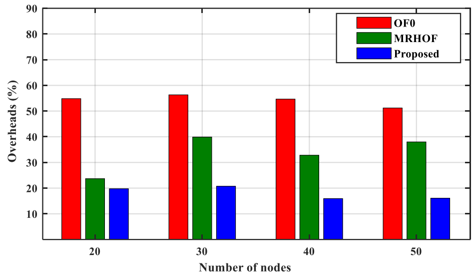

Fig. 3 Total control overhead (%) in different network sizes.

information to use for link-layer routing table entries. An optimization problem has been formulated to generate the RL-based Q-values for DODAG construction. The FRL paradigm is proposed to avoid the overestimation of collision information. We used Contiki 3.0 Cooja simulation to evaluate the proposed scheme. The simulation results indicate the proposed scheme enhances network performance compared to other standard mechanisms.

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