Enhancing IEEE 802.15.4 Access Mechanism with Machine Learning

Arslan Musaddiq, Tariq Rahim, Dong-Seong Kim
ICT Convergence Research Center,
Kumoh National Institute of Technology, Gumi-si, South Korea.
(arslan, dskim)@kumoh.ac.kr, tariq@ieee.org

***Abstract*—The Internet of Things (IoT) network consists of resource-constrained tiny devices. An efficient channel access mechanism for densely deployed IoT devices operating in a lossy environment is one of the major challenges for future IoT networks. The IoT nodes using IEEE 802.15.4 MAC protocol increase the backoff exponent (BE) during the channel sensing period. This blind increase of BE and contention window (CW) before frame transmission affects the network performance. Therefore, in this paper, we propose to use machine learning such as a reinforcement learning (RL) mechanism to handle channel access mechanisms efficiently. The proposed mechanism is evaluated using Contiki 3.0 Cooja simulations. The simulation results indicate that the proposed RL-based mechanism enhances the network performance.**

Keywords—IoT; MAC; IEEE 802.15.4; channel access

I. Introduction

Wireless networks have become increasingly popular particularly the Internet of Things (IoT) networks have vast application areas. IoT network composed of constrained-resource devices that transmit data in a lossy environment. The reliable transmission using advanced digital coding techniques in the physical (PHY) and medium access control (MAC) plays an important role in successful IoT communication. MAC layer particularly affects system-level aspects such as throughput, reliability, fairness, and so on [1]. MAC layer is mainly responsible to provide coordination among wireless nodes for channel contention. Random access mechanism is especially used for low-cost devices because it does not require a centralized coordinator and resources can be allocated in a distributed manner. The carrier-sensing multiple access with collision avoidance (CSMA/CA) protocol is the most widely used multiple access technique. In CSMA/CA, a station continuously senses the channel for contention, and defer for a random time interval if it detects an ongoing transmission to avoid collisions [2].

The IEEE has defined two standards based on CSMA/CA protocol. The IEEE 802.11 standardized MAC layer for the wireless local network (WLAN) uses distributed coordinated function (DCF). In the DCF mechanism, the station first senses the channel. If the channel is busy, it waits for a random backoff time to sense the channel again. If it is found idle, it waits for a short duration known as DCF interframe space (DIFS). Then, it selects a contention window (CW) between a random number 0 to $2^{BE}-1$. Where BE is backoff exponent. The value of BE starts from 0 and increments by 1 each time there is a collision. The maximum backoff stage value is 5. If the channel is empty the station transmits the request to send (RTS) packet and waits for a short duration known as short interframe space (SIFS) to receive clear to send (CTS). After receiving CTS, it transmits a frame. If the acknowledgement (ACK) is received the transmission is successful, if no ACK is received the station increment BE counter by 1. If the retransmission attempt is less than the maximum allowable attempts the STA retransmits the frame. The traditional IEEE 802.11 standard does not have any energy minimization mechanisms which is necessary for scarce resource IoT devices [3].

Another IEEE standard based on CSMA/CA is IEEE 802.15.4 [4]. The IEEE 802.15.4 standard is one of the key enabling technologies for devices that require low-power, high reliability, low cost, and low computation. The IEEE 802.15.4-based IoT devices have been deployed massively in numerous application areas such as smart cities, smart industries, or smart healthcare. The IoT network is made up of a number of IoT sensors and a sink node connected in the form of a graph. The data from various IoT sensors are propagated to the sink node in a multi-hop fashion. With each transmission, the device consumes valuable resources. For example, the IoT device's radio interface is a fundamental source for energy utilization. The maximum energy is consumed during the transmission (Tx) and reception (Rx) phases. Even in the idle state a considerable amount of energy is consumed as CPU is continuously reading the data to measure the channel status [5].

In IEEE 802.11 DCF mechanism node continuously senses the channel during BE period. In IEEE 802.15.4, the channel is sensed only once at the end of BE period. In this way, a node can activate sleep mode for power saving during BE period. The one-attempt sensing does not show major performance benefits in terms of energy-saving rather it fails to handle collision if network size increases. Whenever there is a collision the BE is incremented by 1. If the frame is successfully transmitted the BE is initialized to its minimum value. We can utilize machine learning such as the reinforcement learning (RL) mechanism to create Q-values for BE decisions. In this way, we can intelligently select BE and CW size before frame transmission. In this paper, we are utilizing Q-learning which is one of the RL mechanisms to optimize the channel access mechanism of IEEE 802.15.4.

II. PROPOSED RL-BASED MAC FRAMEWORK FOR IEEE 802.15.4

A. System Model

The proposed technique is based on the Q-learning model to enhance to IEEE 802.15.4 MAC operation. In the proposed algorithm the IoT node is the agent. Each agent has a set of states, i.e., $S = \{s_0, s_1, \dots, s_n\}$. Furthermore, each agent also has a set of actions, i.e., $A = \{a_0, a_1, \dots, a_n\}$. In Q-learning, each agent performs a certain action $a \in A$ in a particular state $s \in S$. With each action there is a reward r. Based on the obtained reward, the agent moves to the next state. For each state-action pair, the agent creates a Q-value. The "Q" in Q-learning stands for quality. It represents how good is it to take the action in a state. There are M number of nodes (agents) which are divided into a set of parents and child nodes, i.e., $M = PUC$, where P represents a set of parent nodes and C represents the set of child nodes.

B. Reinforcement Learning

Machine learning in a wireless communication system is an active research area [6]. Particularly, RL has proven its capabilities to enhance wireless network communication capabilities. In the wireless communication domain, RL has been utilized successfully for cognitive radios, channel access for WLANs, and route optimization in IoT networks. In RL, the agent or device performs the action in a particular state and receives a reward. The agent then creates an estimated value function indicating the state status. The agent's aim is to maximize the reward over time. Q-learning is one of the promising RL techniques that is proven to be effective in solving problems in a resource-constrained environment. Thus, we utilize it to optimize IEEE 802.15.4 MAC layer operation.

C. Proposed Mechanism

This subsection presents our proposed mechanism to enhance IEEE 802.15.4 channel access mechanism for IoT networks. IEEE 802.15.4 has three variables, BE, number of backoffs (NB), and CW. The value of BE is set to 3 initially and the maximum backoff stages are 5. These BE values are standardized by IEEE 802.15.4. The node waits for a random number of BE period in the range of $2^{BE} - 1$. During this BE period, the node performs a clear channel assessment (CCA). If the channel is sensed to be free the transmission starts, if the channel is busy, the node defers the transmission and increases the BE period [7]. In comparison to IEEE 802.11, the BE is increased prior to the frame transmission in IEEE 802.15.4. The IEEE 802.15.4 simply increases the BE each time the channel is found busy. In IEEE 802.11 MAC, the BE is incremented after the collision is detected. Incrementing BE during channel sensing is less energy-consuming than after the end of current transmission. However, this mechanism performs poorly if network density or traffic transmission rate increases. Similarly, If BE is incremented and there is no collision during transmission, then it adds unnecessary BE delays resulting in the degradation of the network performance. The proposed protocol improves BE selection mechanism using the RL mechanism. In the proposed mechanism, the action is the increment or decrement in the BE period. The CW represents the state of the agent in the proposed mechanism. With each action, there is a corresponding reward. The reward is either +1 if there is no collision or -1 if a collision occurs. The node generates a Q-value for each state-action pairs as follows:

$$Q(s_{t+1}, a_{t+1}) = (1 - \alpha) \times Q(s_t, a_t) + \alpha \times \Delta Q(s_t, a_t), \qquad (1)$$

where $0 \leq \alpha \leq 1$ is the learning rate. It represents the weights given to new values compared to the previous one. The improved learning estimate $\Delta Q(s_t, a_t)$ is defined as follows:

$$\Delta Q(s_t, a_t) = \{r_t(s_t, a_t) + \beta \times max_a Q(s', a)\}, \qquad (2)$$

where $0 \leq \beta \leq 1$ is the discount factor. If the value of β is high, the agent gives more weight to future rewards compared to the current reward. In IEEE 802.15.4, if the channel is busy, the BE increments. In the proposed mechanism, we utilize the Q-value during this decision. Q-learning uses an exploration and exploitation procedure. In exploitation phases, during channel sensing, the best BE and CW will be selected using corresponding Q-values which means there is a possibility that BE will not be incremented even if the channel is busy.

Algorithm 1: Enhancing IEEE 802.15.4 Access Mechanism

```
while the device is on do
1.  Initialize DODAG according to RPL mechanism
2.  Set BE = 3, NB = 0, CW = 1, current reward = 0,
    ΔQ (s,a) = 0, and Q(s,a) = 0
3.  Wait for a random period between 0 to 2^BE − 1.
4.  Sense the channel
5.  if channel (busy), then
6.  BE = BE + 1
7.  NB = NB + 1
8.  if (NB > NBMAX), then
9.  failure
10. else
11. Perform CCA
12. Transmit frame
13. if (collision), then
14. reward = −1
15. else
16. reward = +1
17. end if
18. Update reward table r_t(s_t, a_t) for current BE and CW
19. Calculate improved estimate ΔQ(s_t, a_t) according to (2)
20. Update Q-value table using (1),
21. explore and exploit,
22. if (explore), then
23. select BE according to IEEE 802.15.4 mechanism (go to
    step 3)
24. if (exploit), then
25. select BE value from Q-table
26. end if
27. return CW
28. end while
```

III. Performance Evaluation

Table I. Simulation Parameters

Parameters	Value
Simulator	Cooja
Mote device model	Z1 Zolertia
PHY & MAC protocol	IEEE 802.15.4
CW_{min}	0
CW_{max}	31
Maximum backoff stage (BE_{max})	5
Number of backoffs NB_{max}	4
Maximum retransmission limits	3
Network size	20 - 60
Script text analysis	Python 3.7

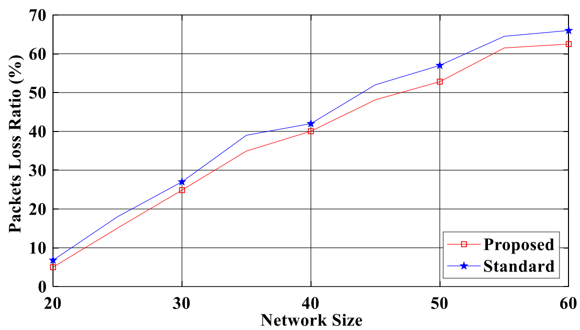

Fig. 1. Packets loss ratio (%) comparison of proposed and standard IEEE 802.15.4 MAC mechanism in a network size of 20 to 60 nodes.

We evaluated our proposed mechanism using the Contiki OS Cooja simulator [8]. The network follows RPL-based DODAG construction. There is one sink node and a number of client nodes. Nodes are based on Zolertia Z1 [9] platform and produce random traffic patterns. The detailed simulation parameters are defined in Table I.

Fig. 1 shows the packet loss ratio (PLR) of the standard protocol compared to the proposed mechanism. The proposed mechanism optimizes the access mechanism even in a dense network of 60 contending nodes. The performance improvement indicates that the Q-learning is effective at learning the access mechanism. Similarly, Fig. 2 shows the channel access delay (in milliseconds). The channel access delay is the amount of time a frame takes from transmission to acknowledgment reception. This delay does not include a delay of dropped frames. From the simulation, we observed the access delay is reduced if BE is selected from Q-table instead of increasing it blindly during sensing period. Thus, the current IEEE 802.15.4 access mechanism does not allow IoT-based networks to achieve high performance.

IV. Conclusion

The IoT network consists of resource-constrained devices operating in a lossy environment. Communication protocols particularly the MAC layer affect system-level aspects such as network reliability, delay, and so on. Currently, the IEEE 802.15.4-based MAC layer blindly increases the BE period if

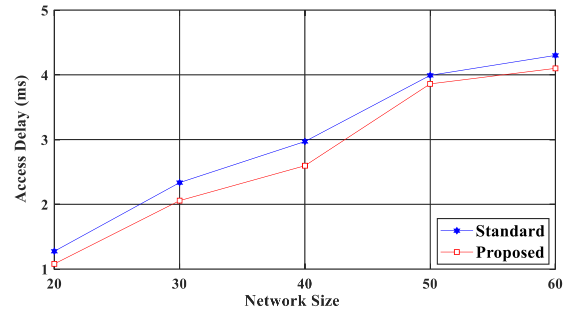

Fig. 2. Access delay (ms) comparison of proposed and standard IEEE 802.15.4 MAC mechanism in a network size of 20 to 60 nodes.

channel is found busy. If the network size increases, the performance degrades. In this paper, we studied the IEEE 802.15.4 channel access mechanism. We investigated the benefits of using ML technique to intelligently optimize the access mechanism. The proposed mechanism learned the BE information to make intelligent frame transmission decisions. The proposed mechanism uses Q-learning to optimize the performance of IEEE 802.15.4. The simulation results indicated the proposed mechanism improves the network performance.

Acknowledgment

This research was financially supported by the MSIT (Ministry of Science, ICT), Korea, under the Grand Information Technology Research Center support program (IITP-2020-2020-0-01612) supervised by the IITP (Institute for Information & communications Technology Planning & Evaluation), and Priority Research Centers Program (2018R1A6A1A03024003) through the National Research Foundation of Korea (NRF) funded by the Ministry of Education, Science and Technology.

References

[1] A. Musaddiq, Y. B. Zikria, O. Hahm, H. Yu, A. K.Bashir et al., "A survey on resource management in IoT operating systems," IEEE Access, vol. 6, pp. 8459–8482, 2018.

[2] IEEE802.org. (2018). IEEE P802.11—TASK GROUP AX. Accessed: Jun. 11, 2021. [Online]. Available: http://www.ieee802.org/.

[3] G. Bianchi, "Performance Analysis of the IEEE 802.11 Distributed Coordination Function," IEEE Journal on Selected Areas in Communications, vol. 18, no. 3, pp. 535-547, 2000.

[4] LAN/MAN Standard Committee (2006) Part 15.4: Wireless Medium Access Control (MAC) and Physical Layer(PHY) specifications for low-rate wireless personal area networks. IEEE 802.15.4. Std

[5] A. Musaddiq, Y. B. Zikria, Zulqarnain, and S. W. Kim, "Routing protocol for low-power and lossy networks for heterogeneous traffic network," *Journal on Wireless Communications and Networking*, vol. 2020, no. 1, pp. 1–23, 2020.

[6] M. S. Mahdavinejad, M. Rezvan, M. Barekatain, P. Adibi, P. Barnaghi et al., "Machine learning for Internet of Things data analysis: A survey," Digital Communication and Networks, vol. 4, no. 3, pp. 161–175, 2018.

[7] H. Tall, G. Chalhoub and M. Misson, "Implementation and performance evaluation of IEEE 802.15.4 unslotted CSMA/CA protocol on Contiki OS," Annals of Telecommunications, no. 9-10/2016, 2016.

[8] Contiki, "Contiki: The open source operating system for the Internet of Things," 2015. [Online]. Available: http://www.contiki-os.org/.

[9] Zoleartia, "Z1 datasheet," 2010. Available: http://www.zolertia.com/.