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RESEARCH ARTICLE

Performance Evaluation of Reinforcement Learning Based Distributed Channel Selection Algorithm in Massive IoT Networks

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ABSTRACT In recent years, the demand for new applications using various Internet of Things (IoT) devices has led to an increase in the number of devices connected to wireless networks. However, owing to the limitation of available frequency resources for IoT devices, the degradation of the communication quality caused by channel congestion is a practical problem in developing IoT technology. Many IoT devices have hardware and software limitations that prevent centralized channel allocation, and congestion is even more severe in massive IoT networks without a central controller. Therefore, developing a distributed and sophisticated channel selection algorithm is necessary. In previous studies, the channel selection of each IoT device was modeled as a multi-armed bandit (MAB) problem, and a wireless channel selection method based on the MAB algorithm, which is a simple reinforcement learning, was proposed. In particular, it has been shown that the MAB algorithm of tug-of-war (TOW) dynamics can efficiently select channels with much lower computational complexity and power compared with other reinforcement learning-based channel-selection methods. This paper proposes a distributed channel selection method based on TOW dynamics in fully decentralized networks. We evaluate the effectiveness of the proposed method and other distributed channel-selection methods on the communication success rate in massive IoT networks by experiments and simulations. The results show that the proposed method improves the communication success rate more than other distributed channel selection methods even in a dense and dynamic network environment.

INDEX TERMS Channel selection, low power consumption, massive IoT system, reinforcement learning.

I. INTRODUCTION

In recent years, Internet of Things (IoT) technology has become commonplace in a variety of fields such as smart cities [1], medicine [2], and agriculture [3]. The number of IoT devices in the world is predicted to reach approximately 35 billion by 2022, with continued growth expected thereafter [4]. In an IoT network consisting of a large number of devices, even if the volume of data obtained from an individual device is low, new services are expected to acquire large

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volumes of data in real-time using this extensive distribution of devices [5], [6].

Conversely, in an environment where there is a high density of IoT devices, network congestion and changes in topology and components due to the movement of devices are likely to become a problem, which may significantly degrade the quality of communication [7]. Therefore, a major challenge is guaranteeing high-quality communication amongst IoT devices under limited frequency resources. A potential solution to this problem is the application of multi-channel wireless communication technology, which allows each device to select or assign a channel with a low connection load in the same wavelength band [8], [9]. In multi-channel communication, each IoT device selects a channel with the least possible connection load from the multiple available channels, thereby enabling efficient and stable communication even in an environment with a high density of IoT devices.

A centralized channel allocation system has been proposed as a method of allocating the radio channel to be used by each device in a multi-channel system [10], [11]. This system can achieve a high communication success rate by controlling transmission and reception timing throughout the network. However, it is necessary to implement complex algorithms to ensure that all devices in the network are precisely time-synchronized and communicate according to scheduling rules. This feature requires devices with large storage capacity and high computing power. Yet, many IoT devices are intended to collect various data types with low power consumption and small storage capacity. Therefore, each IoT device needs to perform channel selection asynchronously and in a distributed system. Also, the conventional distributed channel selection method is not suitable for IoT devices, which are low power devices, because each channel state needs to be sensed at a certain time interval [12]–[14]. In [15] and [16], a distributed method was proposed in which each device selects a channel and other parameters based on deep learning. In these methods, various state information at each time step can be obtained from the external environment, and learning proceeds based on deep learning, which includes complex processing to achieve high performance. However, as highlighted earlier, most IoT devices have low power consumption and small storage capacity, which makes it difficult to acquire the various state information of the surroundings and implement complex algorithms. Therefore, a learning method with a reduced learning cost is required.

In [17] and [18], channel assignment to each device was modeled as a multi-armed bandit (MAB) problem [20], and a channel access method was proposed. The MAB problem is a decision-making problem in which a player selects a machine to obtain the maximum reward in the presence of multiple machines. Several algorithms have been proposed to solve the MAB problem, including the ϵ-greedy [21], upper confidence bounds (UCB) [22], [23], and tug-of-war (TOW) dynamics. In particular, TOW dynamics, proposed in [24]–[27], has already been demonstrated to achieve higher performance than other MAB algorithms, despite the simple quadrature learning rule.

In [28]–[31], TOW dynamics-based channel selection algorithms were implemented in devices and evaluated for their effectiveness in various environments, such as cognitive radio systems, wireless LANs (WLAN), and IoT networks. Furthermore, in [30] and [31], it was shown that by introducing two types of forgetting factors into TOW dynamics, the algorithm can dynamically and smoothly follow the changes in the communication environment. However, these studies focused on uplink communications in centralized IoT systems, where each device selects one of the common access points and cannot support fully decentralized wireless networks where the environment is more dynamic. In decentralized wireless networks, it is necessary to select a common channel with other devices simultaneously. However, selecting the same channel among communicating devices is challenging without exchanging channel state information: i.e., a novel distributed channel selection method is needed to solve this problem.

Motivated by the aforementioned technical background, this paper proposes a distributed channel selection method based on TOW dynamics with forgetting factors for decentralized IoT networks. Therefore, our goal is to improve the success rate of communication in such environments by using a channel-selection algorithm based on reinforcement learning in each device. The distinctive contributions of this study are as follows:

- In this work, we propose a distributed channel-selection algorithm based on TOW dynamics with forgetting factors and show that it can achieve high communication success rates even in fully decentralized networks.
- We implement the proposed algorithm on an IoT device (Lazurite Pi Gateway [32]), and conduct experiments to show that the proposed channel selection algorithm based on TOW dynamics can function in the real world. The experimental results show that the proposed algorithm improves the communication success rate compared to the ϵ-greedy algorithm and random frequency hopping.
- Furthermore, to evaluate the performance of the proposed algorithm in a large-scale fully decentralized network environment, we conduct simulation experiments using Network Simulator 3 (NS3) and real data of vehicles. We show that the proposed algorithm avoids congestion and improves communication success rate even in a high-density network environment where the channel state changes in various scenarios.

The remainder of this paper is organized as follows. Section II introduces the conventional distributed channel-selection algorithm. In Section III, we present the decentralized IoT system model used in this study. Section IV presents the proposed method in this paper. Further, Section V details how the model is implemented in low-power devices and evaluates the implemented IoT devices through experiments.

TABLE 1. Acronyms and abbreviations.

Acronym or abbreviation	Writing out in fill
IoT	internet of things
MAB	multi-armed bandit
UCB	upper confidence bounds
TOW	tug-of-war
ACK	acknowledgement packet
RANDOM	random frequency hopping
AFH	adaptive frequency hopping
FSR	frame success rate

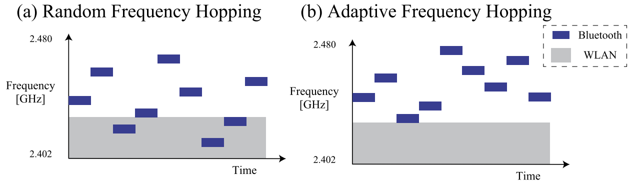

FIGURE 1. Interference when WLAN and Bluetooth are operating simultaneously.

After a simulation-based evaluation for a channel-selection problem in massive IoT environments is provided in Section VI, we present a different simulation-based evaluation using real data of vehicle location information in Section VII. Finally, Section VIII concludes the paper and discusses future issues.

Note that acronyms and abbreviations are summarized in Table 1.

II. RELATED WORKS

This section introduces related works on distributed channel selection methods for IoT devices.

A. ADAPTIVE FREQUENCY HOPPING

With the evolution of wireless protocols and access technologies in the unlicensed Industrial, Scientific and Medical (ISM) band, various devices are competing for the common spectrum, and interference is increasing [19]. Bluetooth is a short-range wireless technology in the 2.4 GHz ISM band, which has channel selection with pseudo-random frequency hopping to reduce interference with other wireless devices. Adaptive frequency hopping (AFH) detects static sources of interference, further improving immunity to interference. Fig. 1 shows the interference when WLAN and Bluetooth are operating simultaneously. AFH evaluates each channel's received signal strength indication (RSSI) and packet error rate (PER) to identify channels that interfere with other devices. By removing them from the list of available channels, AFH can adapt to a dynamic environment.

Conversely, AFH is designed to identify and exclude static sources of interference. Therefore, if there is a high density of frequency hopping devices, interference occurs as usual. Further, AFH needs to sweep all channels to update the list of available channels at a certain time interval. This means that the network overall consumes extra energy.

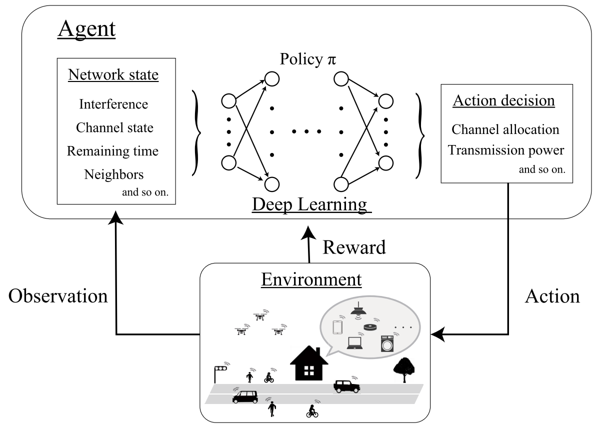

FIGURE 2. Framework of deep learning approach.

B. DEEP LEARNING APPROACH

To adapt to a large-scale dynamic environment, a distributed resource allocation method based on deep learning has been proposed [15], [16]. Fig. 2 shows the framework of deep learning, which consists of interactions between agents and the environment. Each agent retrieves various information and updates it based on policies to select actions that satisfy a lot of quality-of-service (QoS) requirements.

Conversely, some IoT devices cannot acquire a lot of information due to location limitations. Also, low power consumption and small storage capacity devices are difficult to execute complex algorithms.

C. MAB ALGORITHM APPROACH

The MAB (Multi-Armed Bandit) problem [20] determines the optimal strategy to earn maximum rewards by playing multiple machines with unknown reward probabilities in limited times. It is a statistical model that balances exploration and exploitation to solve recurring decision problems. There are several algorithms for solving MAB problems, such as the ϵ-greedy [21] and upper confidence bounds (UCB) [22], [23]. In addition to the conventional methods, TOW dynamics [24]–[27] is a very simple and low calculation algorithm, yet it has been shown to perform as well as UCB1-tuned [24].

In [30] and [31], the channel selection problem for each IoT device is modeled as a MAB problem, where the available channel $k \in K$ is the machine and the ACKnowledgement (ACK) frame received upon successful communication is the reward. The details of each algorithm are shown below.

1) ϵ-GREEDY [21]

ϵ-greedy is a method in which the trade-off between exploitation and exploration is determined by the parameter ϵ. It is an algorithm that utilizes the machine with the highest reward probability obtained from past experience with probability $1-\epsilon$ while randomly selecting another machine with probability ϵ to search. The machine k^* to be selected at each time step is represented by the following equation, using the reward probability p_k:

$$p_k(t) = \frac{r_k(t)}{n_k(t)}, \tag{1}$$

$$k^* = \begin{cases} \arg\max\limits_{k=1\sim K} p_k(t), & \text{with probability } 1-\epsilon. \\ \text{a random action}, & \text{with probability } \epsilon. \end{cases} \tag{2}$$

where $k \in (1, 2, \ldots, K)$. n_k is the accumulated count of selections of machine k, and r_k is the accumulated count of rewards of machine k until time t.

2) UPPER CONFIDENCE BOUNDS [22], [23]

UCB1 is an algorithm that makes decisions based on the UCB value, which is a combination of the reward probability of each machine and the uncertainty of its evaluation. The machine k^* to be selected at each time is expressed by the following equation:

$$k^* = \arg\max_{k=1\sim K} \left(p_k(t) + \sqrt{\frac{2\log N}{n_k(t)}} \right). \tag{3}$$

where N is the total number of trials on all machines.

Furthermore, UCB1-tuned has been proposed as a higher performance algorithm than UCB1, although there is no theoretical guarantee. UCB1-tuned is an algorithm that considers the variance in addition to the reward probability; the following equation expresses this algorithm:

$$V_k(n_k) = \hat{\mu_k} + \sqrt{\frac{2\log N}{n_k(t)}}, \tag{4}$$

$$k^* = \arg\max_{k=1\sim K} \left(p_k(t) + \sqrt{\frac{\log N}{n_k(t)} \min\left(\frac{1}{4}, V_k(n_k)\right)} \right). \tag{5}$$

where $\hat{\mu_k}$ is the variance of the acquired reward at machine k.

3) TOW DYNAMICS [24]–[27]

The TOW algorithm based on TOW dynamics is a reinforcement learning algorithm inspired by the behavior of amoebas [24]–[27]. Whereas other MAB algorithms update the reward probability of each machine in each trial, TOW dynamics update the estimates of all machines simultaneously based on the volume conservation law. TOW dynamics is a learning policy based on the reward estimate Q_k, which is expressed as follows,

$$Q_k(t) = Q_k(t-1) + \Delta Q_k(t), \tag{6}$$

$$\Delta Q_k(t) = \begin{cases} +1 & \text{if the ACK received}, \\ -\omega & \text{if not the ACK received}. \end{cases} \tag{7}$$

$$\gamma = p_{1\text{st}(t)} + p_{2\text{nd}(t)}, \tag{8}$$

$$\omega = \frac{\gamma}{2-\gamma}, \tag{9}$$

where $p_{1\text{st}}$ and $p_{2\text{nd}}$ represent the top two reward probabilities among all machines and are calculated by (1). ω is obtained mathematically using these two reward probabilities as the optimal weighting parameters.

Decision making with TOW dynamics is performed based on the height of the fluid interface X_k of each machine expressed as follows, using Q_k in (10). In addition, the machine that will be selected in the subsequent trial will be the machine for which X_k is the largest.

$$X_k(t) = Q_k(t-1) - \frac{1}{K-1} \sum_{k^* \neq k}^{K} Q_{k^*}(t-1) + osc_k(t), \tag{10}$$

$$k^* = \arg\max_{k=1\sim K} X_k(t), \tag{11}$$

where osc is an autonomous oscillation for each slot machine according to (12). There are many possibilities for adding oscillations. For simplicity, we used $A = 0.5$ for all machines in this study.

$$osc_k(t) = A\cos\left(\frac{2\pi t}{K} + \frac{2(k-1)\pi}{K}\right). \tag{12}$$

4) TOW DYNAMICS WITH FORGETTING FACTOR [30], [31]

In [30] and [31], it is proposed to introduce forgetting factors into TOW dynamics. It has shown that the introduction of forgetting factors leads to accurate and adaptive decisions to select the appropriate channel even when the environment changes. Thus, the success frame ratio of the network is improved [30].

MAB algorithm-based distributed channel selection method can be implemented in hardware and software limited IoT devices, and it can improve the communication success rate and provide fair channel connection opportunities [30], [31]. However, these studies focused on uplink communication in a centralized IoT system, where each device selects one of the shared access points. Therefore, it is necessary to evaluate them in a more dynamic environment.

III. SYSTEM MODEL

We focus on fully decentralized networks composed of mobile IoT devices, which are expected to lead to the development of various applications; such as emergency networks, ITS applications [34] and a new trend in the IoT, namely the Internet of Wearable Things (IoWT) [35]. This paper assumes a distributed massive IoT system consisting of M IoT devices in an area S, as shown in Fig. 3. In this system, each device can select and use one of the multiple channels $k = \{1 \ldots 3\}$ that do not interfere with each other at each time. It is possible to send and receive data by sharing a common channel among several devices. The communication flow involves building a fully decentralized network among devices. Each device selects one of the available channels and sends and receives data from devices using the common channel.

Fig. 4 shows the three conditions under which communication quality can be degraded in a massive decentralized IoT system. The first condition is whether devices use the same channel. The communication between devices succeeds

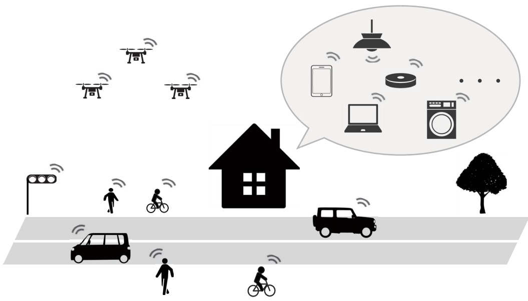

FIGURE 3. System model.

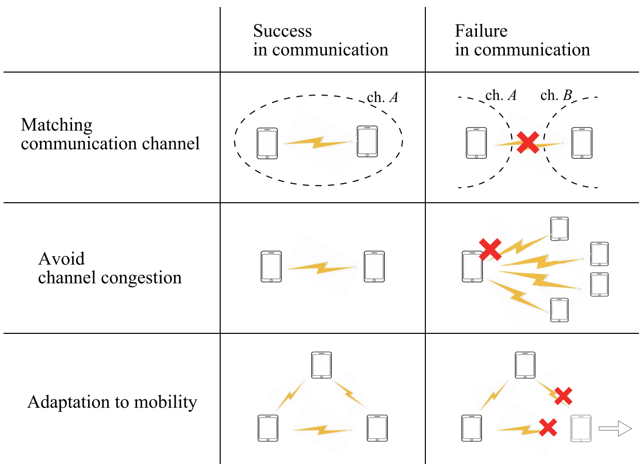

FIGURE 4. Conditions for successful communications.

if they use the same channel; otherwise, it fails. The second condition is whether network congestion occurs. In a situation where IoT devices are densely deployed, communication failures will frequently occur due to the concentration of connections. The third condition is whether the connection between devices disconnects due to user movement. In addition, as the channel state changes and devices move, the available channels for communication and neighboring nodes may change over time. To avoid these conditions, it is necessary to have a channel selection method that can respond quickly to the dynamically changing environment and maintain a high communication success rate for each device.

IV. PROPOSED METHOD

In this paper, we propose a distributed channel selection method based on TOW dynamics for fully decentralized networks. As described in Section III-A, in fully decentralized networks, the conditions for successful communication change depending on the surrounding environment, so a novel distributed channel selection method is needed. Therefore, based on [30], [31], we propose a distributed channel selection method by introducing two forgetting factors into the TOW dynamics, which can respond to dynamic changes in the surrounding environment, such as fully decentralized networks. Each forgetting factor is described as follows:

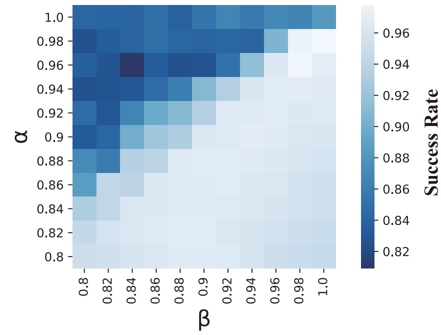

FIGURE 5. Impacts of introducing forgetting factor. (Preliminary experiment: the case of 30 devices deployed.)

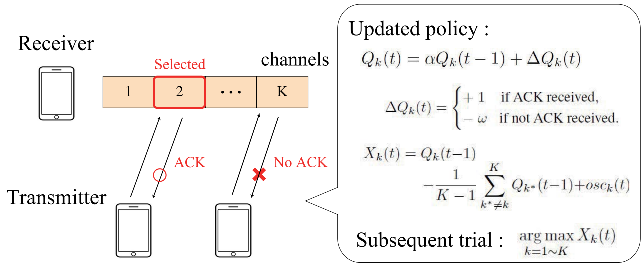

FIGURE 6. Updated policy of TOW dynamics-based channel selection method.

The first forgetting factor α ($0<\alpha<1$) is used to control the influence of past experience. Then, the reward estimate Q_k in (6) is rewritten as follows:

$$Q_k(t) = \alpha Q_k(t-1) + \Delta Q_k(t), \tag{13}$$

The forgetting factor α controls the scale of past estimates to deal with sudden changes in the communication environment with fewer trials.

The second forgetting factor, β ($0<\beta<1$) is used to control the communication success rate. It is proposed that p_k and n_k be updated as follows: as the number of trials increases, the impact of success or failure on the communication success rate decreases.

$$r_k(t) = \begin{cases} 1 + \beta r_k(t-1) & \text{if } k = k^* \text{ and the ACK received,} \\ \beta r_k(t-1) & \text{otherwise.} \end{cases} \tag{14}$$

$$n_k(t) = \begin{cases} 1 + \beta n_k(t-1) & \text{if } k = k^*, \\ \beta n_k(t-1) & \text{otherwise.} \end{cases} \tag{15}$$

Fig. 5 shows the impacts of introducing forgetting factors when there is a dynamic change in the preliminary experiment. The selection of parameters faces a trade-off between a large parameter that makes it difficult to follow changes and a small parameter that does not enable sufficient learning. In this paper, based on the results of various preliminary experiments, we select forgetting factors that work best in the $1 \sim 0.9$ for both factors.

Fig. 6 shows the updated policy of the channel selection method based on TOW dynamics. By appropriately setting

FIGURE 7. Mobile IoT prototype.

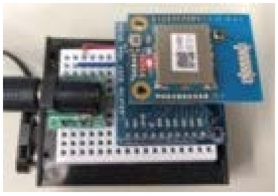

FIGURE 8. IoT device.

TABLE 2. Implementation parameters.

Parameters	Value
Frequency band	920 MHz
Number of Lazurite Pi GateWay	5 fixed, 2 on the bicycle
Transmission interval of Lazurite Pi GateWay	1 s
Number of Lazurite920J (load devices)	14
Transmission interval of Lazurite920J (load devices)	0.1 s
Transmission power of each device	1 mW
Number of channels K	3
Speed of the bicycle	5 ms
Length of one lap L	300 m

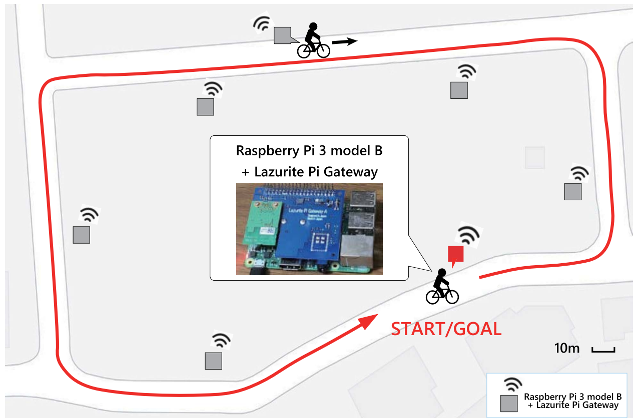

FIGURE 9. Experimental setup 1.

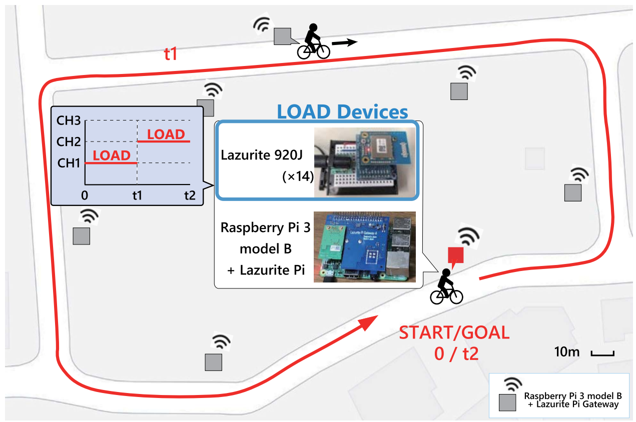

FIGURE 10. Experimental setup 2.

the aforementioned two types of forgetting factors, the IoT device updates X_k of each channel using (10) and selects the channel, $k^* = \arg\max_{k \in K} X_k(t)$ in the subsequent trial. It has been shown that the system can dynamically and smoothly follow dynamic changes. In this paper, we clarify the performance of TOW dynamics with forgetting factors in decentralized IoT networks.

V. EXPERIMENTATION

A. IMPLEMENTATION

As a prototype mobile IoT device, we implemented the proposed algorithm in a device equipped with Lazurite. This wireless module uses the 920 MHz frequency band and Raspberry Pi. Lazurite is equipped with an IEEE 802.15.4g/4e radio-compatible transceiver (AM11DP-ST01) supporting a 50-kbps data rate in the 920-MHz band and an ultra-low-power 16-bit microcontroller (ML620Q504H) with 64 KB ROM. We also used the Lazurite 920 J [32] as the load device, using the same frequency band. The prototype of the mobile IoT device and the load device is shown in Fig. 7 and Fig. 8, respectively.

B. PERFORMANCE EVALUATION

This section presents the performance evaluation results of the channel selection algorithm based on TOW dynamics on IoT devices. Figs. 9 and 10 show the experimental setups. In Fig. 9, five IoT devices are placed and fixed on a road with a circumference of about 300 meters; the other two devices are carried on bicycles. In Fig. 10, in addition to these devices, several devices serve as loads. As a prerequisite, we ensured that the IoT devices on the road placed at each location were fixed at a distance where communication between devices was not possible. Furthermore, we ensured that while one IoT device on a bicycle was communicating with a fixed IoT device, the other fixed IoT devices were at a distance where communication between devices was not possible.

We evaluated the number of packets received by a channel between devices on the road during one lap L of a red IoT device mounted on a bicycle. The experimental parameters are listed in Table 2. We compare the performance of the TOW dynamics-based channel-selection algorithm with other typical MAB algorithms introduced in Section II. The experiments were conducted using the following four methods: (i) Random frequency hopping (RANDOM), (ii) ϵ -greedy, (iii) TOW w/o α and β, and (iv) TOW w/ α and β. The specifics of each experimental setup are as follows: Experiment 1 evaluates the channel selection for

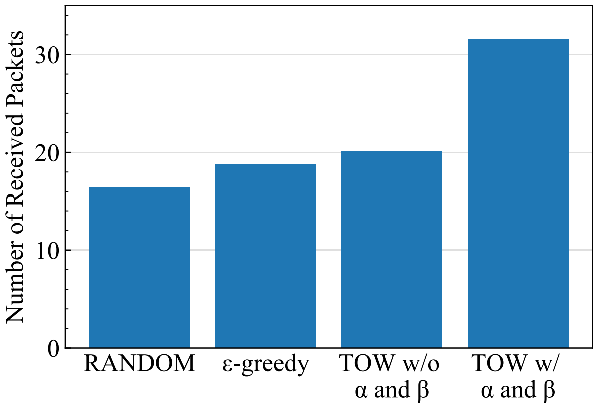

FIGURE 11. Average number of received packets in setup 1.

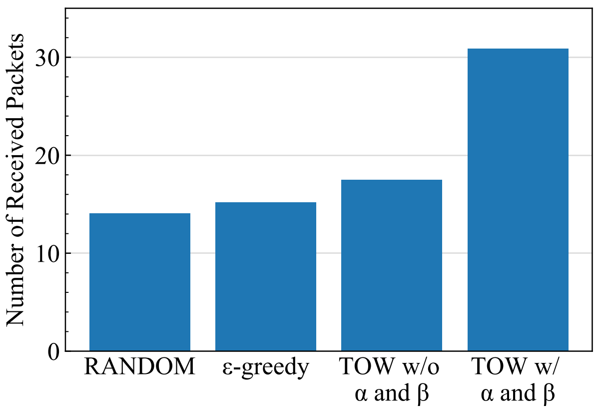

FIGURE 12. Average number of received packets in setup 2.

the mobility of devices in the IoT network. In addition, in Experiment 2, we prepared some load devices to increase the connection load to the channel and set them to change the channel where the connected load is increased when the bicycle dose a half lap. Therefore, Experiment 2 evaluated the mobility of the device and the variation of the communication environment.

Fig. 11 shows that the channel-selection algorithm based on TOW dynamics with or without the forgetting factors has more packets received than the other methods. We assume that TOW dynamics can proceed with learning using estimates for all channels, whereas the other methods proceed only with estimates for the channels used in each trial. Therefore, TOW dynamics can receive more packets than the other methods with more efficient learning. The methods based on TOW dynamics, including the forgetting factors, demonstrated better results. In a situation where the communication environment changes over time due to the movement of devices, the inclusion of forgetting factors allows the system to select an appropriate channel each time.

Fig. 12 shows that the number of arrived packets by each method was reduced compared to the result in Fig. 11, which indicates that it is more difficult to select a communicable channel when the devices are mobile, and the communication

TABLE 3. Simulation parameters.

Parameters	Value
Frequency band	2.4 GHz
Modulation format	O-QPSK
Path loss model	Log distance propagation
Propagation delay model	Constant speed propagation
Fading model	Rayleigh fading
Mobility model	Constant position (scinario 1, 2) Random walk 2d (senario 3)
Transmission power	1 mW
Communication range	100 m
MAC Protocol	CSMA/CA
Frame size	100 byte
Number of channels K	3
Number of IoT devices M	100
Number of load devices	64 (8×8 grid)
Transmission interval of IoT devices	0.2 s
Transmission interval of load devices	0.01 s
Simulation area S	Square of 500 m per side (0.25 km^2)
Simulation time	10 min
ϵ-greedy parameter ϵ	0.1

environment is dynamic. Among them, it was observed that the channel selection algorithm based on TOW dynamics had more arrived packets than the other methods. In particular, the results of TOW dynamics, including the forgetting factors, are similar to those in Fig. 11, which indicates that the method can learn efficiently even when the mobility of the device or the channel state changes.

VI. COMPUTER SIMULATION

This section performs simulations to evaluate the results on a larger scale. The performance of the channel selection algorithm based on TOW dynamics is compared with that of other methods under three evaluation scenarios: (A) devices are present in high density, (B) load devices are mixed, and (C) devices are moving. The implementation experiments were conducted using the following six methods: (i) Random frequency hopping (RANDOM), (ii) Adaptive Frequency Hopping (AFH), (iii) ϵ -greedy, (iv) UCB1-tuned, (v) TOW w/o α and β, (vi) TOW w/ α and β. This simulation assumes that each IoT device selects a channel based on the reinforcement learning algorithm and sends and receives data only from devices that select the same channel. The evaluation index is defined as the frame success rate (FSR) of communication in the entire network, as shown in (16).

$$FSR = \frac{\sum_{i=1}^{M} \sum_{j=1}^{K} r_j^i}{\sum_{i=1}^{M} \sum_{j=1}^{K} n_j^i}, \tag{16}$$

where M is the number of devices, K is the number of available channels, and r_j^i is the number of counts receiving reward (ACK) when node i uses channel j, and n_j^i is the number of counts node i attempts to send using channel j. In this simulation, the LR-WPAN model in Network Simulator 3 (NS3) [33] was used as a network simulator. Each device is randomly placed in the area and transmits data at a

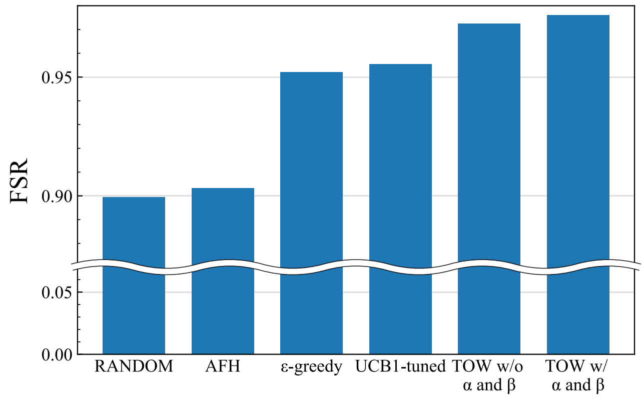

FIGURE 13. FSR in scenario 1.

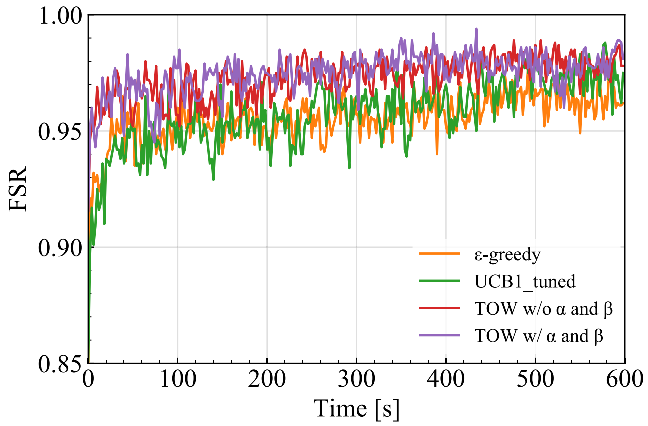

FIGURE 14. FSR at each time step in scenario 1.

certain transmission interval. The simulation parameters are presented in Table 3.

A. SCENARIO 1: DEVICES ARE PRESENT IN HIGH DENSITY

In a situation where IoT devices are densely distributed, the concentration of connections on a particular channel may reduce the communication success rate of the entire network. Therefore, each device must select a channel with a low communication load in such a situation. Fig. 13 shows the FSR of each method and Fig. 14 shows the FSR at each time. Moreover, the forgetting factors α and β in TOW dynamics are set to 0.98 and 0.98, respectively.

Fig. 13 shows that the channel selection methods based on the MAB algorithm provide better FSR than RANDOM or AFH. The AFH, a conventional distributed channel selection method, can exclude static sources of interference such as WLANs. Still, it is not expected to work effectively where hopping devices are densely deployed. In addition, the AFH updates the list of available channels at each preset interval, which results in extra sensing. Conversely, the channel selection methods based on the MAB algorithm provide better FSR even in such a situation because it does not require extra sensing. Fig. 14 shows that the channel selection methods based on TOW dynamics with or without forgetting factors

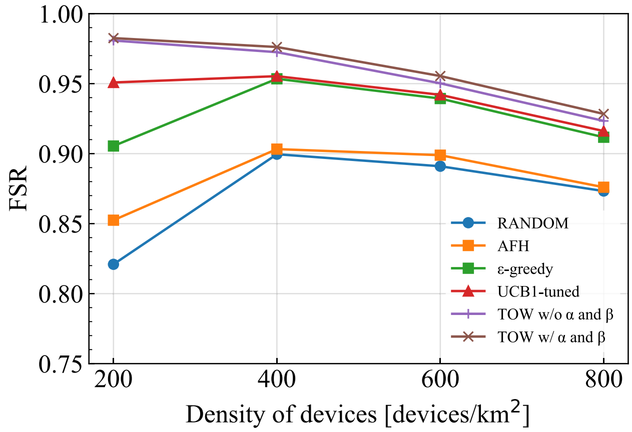

FIGURE 15. FSR by the number of devices belonging to the network (Number of channels: 3).

achieve a higher FSR with fewer trials than the other methods. Also, the channel selection in a distributed system based on the MAB algorithm requires each device to learn the state of each channel and it takes time for the learning to proceed. Conversely, TOW dynamics is a unique algorithm that updates based on the estimates of all channels in each trial; hence, it can achieve a higher FSR with fewer training cycles than other methods.

Fig. 15 shows the results of FSR by the number of devices belonging to the network for each method. The channel selection method based on TOW dynamics offers a better FSR for each device density than the other methods. When the number of devices belonging to a network is small, frequency resources are not a problem; however, it is necessary to select a channel and communicate on a common channel with surrounding devices. In this case, the channel selection method based on TOW dynamics can proceed with learning more efficiently than other methods; it is considered that a higher FSR is obtained by selecting a common channel with the surroundings in fewer trials. Conversely, as the number of devices belonging to the network increases, a single channel often faces congestion owing to simultaneous channel access by multiple devices. Therefore, it is necessary to select a vacant channel that can communicate among the available channels. In this case, the channel selection method based on TOW dynamics can select a vacant channel that can be communicated within a few trials; hence, we assume that it has a higher FSR than the other methods.

B. SCENARIO 2: LOAD DEVICES ARE MIXED

When there are other wireless communication devices (load devices) using the same frequency band in the neighborhood, the communication success rate of the used channel may decrease due to the communication load increase. Therefore, in such a situation, it is necessary to immediately detect a change in the status of the used channel and reselect another channel with a lower load if the communication load is high.

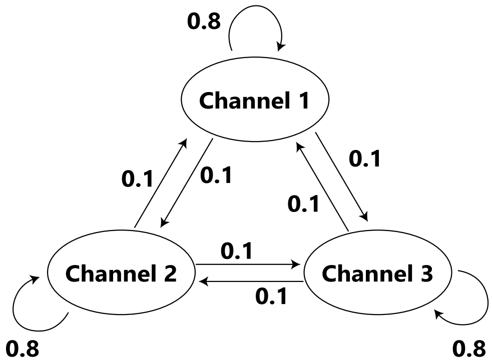

FIGURE 16. Transition probability of highly loaded channel (every 3 seconds).

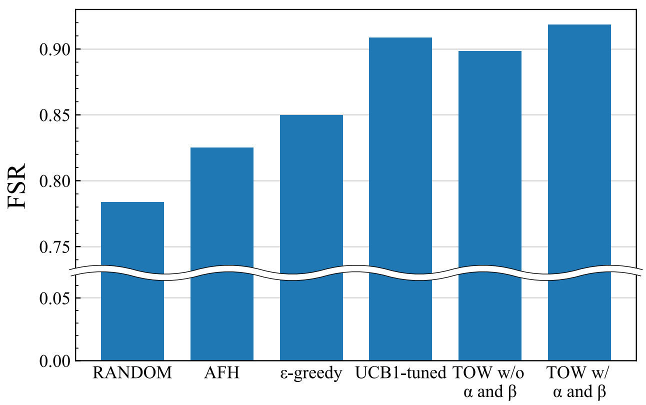

FIGURE 17. FSR in scenario 2.

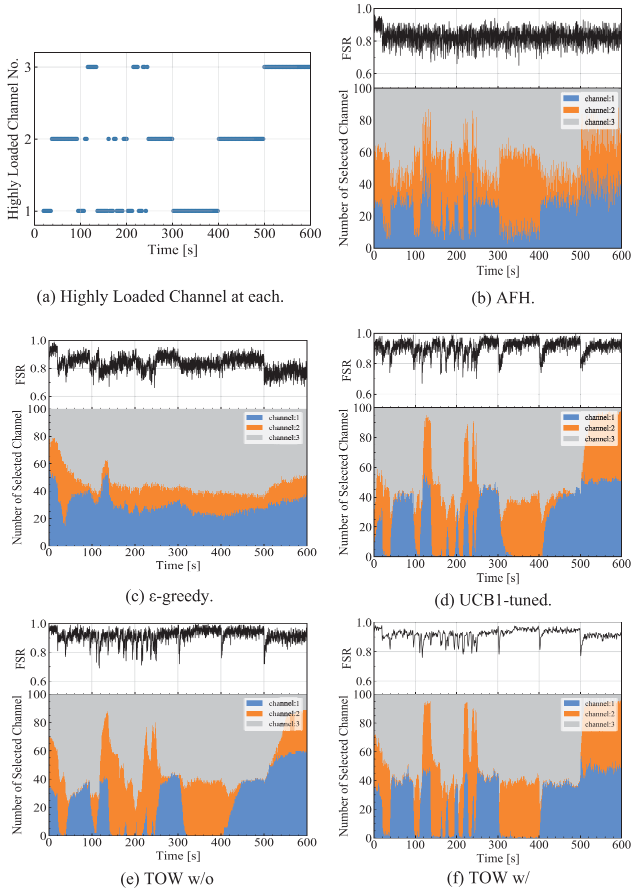

FIGURE 18. Highly loaded channel, the number of selected channels, and the FSR in each method at each time step in one simulation.

In this simulation scenario, in addition to the 100 IoT devices, 64 load devices were placed in an 8×8 grid. Further, the communication area was assumed to be uniformly loaded. As the channels used by load devices interfere with the channels used between IoT devices, it is assumed that congestion will frequently occur if the same channels are selected simultaneously. Twenty seconds after the start of the simulation, the load devices selected a certain channel, and one of the channels was assumed to be loaded at each time. In the first half of the simulation, the loaded channel changed stochastically according to the transition probability, as shown in Fig. 16 to assess if it can respond to the changing channel state. In the second half, the loaded channel changes periodically to assess if it can respond quickly to channel changes even after some simulation time has passed. The FSR results of each method in this environment, where the channel state changes over time, are shown in Fig. 17. Furthermore, this scenario sets the forgetting factors α and β in TOW dynamics to 0.95 and 0.98, respectively.

Fig. 17 shows that the TOW dynamics with forgetting factors based channel-selection method has the highest FSR compared to the other methods when the highly loaded channels are mixed. For the results shown in Fig. 17, we show the change in the highly loaded channel over time for one simulation and the difference in the performance of each method in Fig. 18.

Fig. 18 shows that as the load on a particular channel is increased, the number of devices selecting that channel is decreased, and the number of selected channels that are capable of sufficient communication is increased. The TOW dynamics with forgetting factors based channel selection method can follow the change of channel state even after the number of trials increases. In contrast, other MAB algorithm-based methods cannot do so well. This is because the typical MAB algorithm selects a channel based on past reward acquisition status. Conversely, TOW dynamics with forgetting factors partially forget the past reward acquisition and select a channel based on the current reward acquisition status. Therefore, even if the state of the channel changes after an increase in the number of trials, the channel can be changed to one that provides sufficient reward with fewer trials. Therefore, the channel selection method based on TOW dynamics with forgetting factors can achieve higher FSR than other MAB-based channel-selection methods, as shown in Fig. 17.

Also, Fig. 17 shows that the channel selection method based on the MAB algorithm has a higher FSR than AFH,

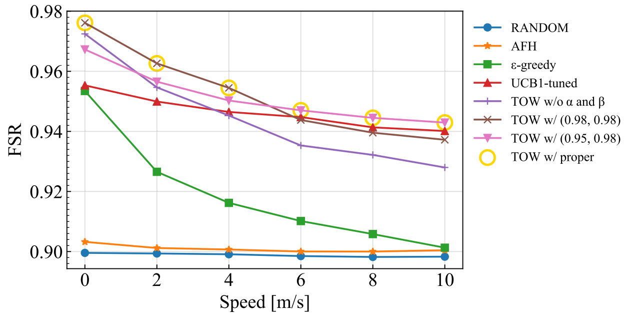

FIGURE 19. Scenario3. FSR for each method when the devices are moving.

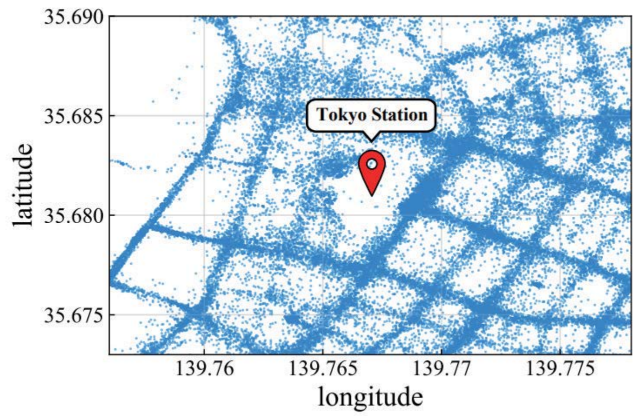

FIGURE 20. Vehicle location data around Tokyo Station.

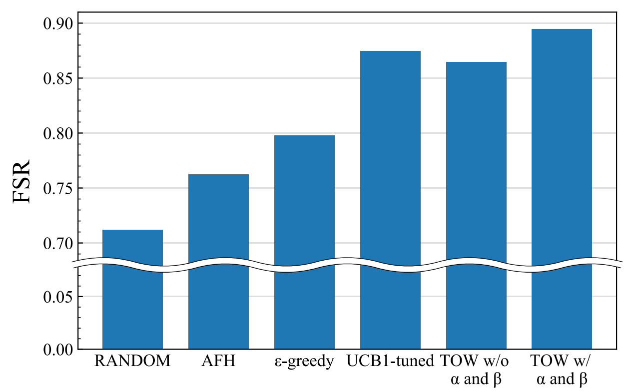

FIGURE 21. FSR in real simulation.

a conventional channel selection method that does not rely on reinforcement learning. Fig. 18 shows that AFH can respond to changes in channel states; however, compared to MAB-based channel-selection methods, the number of devices that select channels with increased load is higher. This is due to the need to update the list of available channels at each preset interval. As a result, extra sensing occurs and the FSR is lower than MAB-based channel-selection methods.

C. SCENARIO 3: DEVICES ARE MOVING

In decentralized wireless networks, the network topology changes as the IoT devices move, and the surrounding environment is different after the change, which may reduce the communication success rate in the previously used channel. Therefore, each IoT device needs to select an appropriate channel according to the changes in the network topology.

In this subsection, each IoT device is assumed to move in a random direction within a 500 m square. In addition, the forgetting factors of the TOW dynamics were simulated with several parameters, and the situation with the highest FSR was measured and labeled as TOW w/ proper. Fig. 19 shows the FSR of each method.

Fig. 19 shows that the FSR of the TOW-based channel selection method with forgetting factors is the highest at each speed. This is because as the device moves and the topology changes, the method forgets the past reward acquisition status and can learn more efficiently. We can confirm that the forgetting factor α changes from 0.98 to 0.95 when the highest FSR is recorded at the speed of $4 \sim 6$ m/s for each device. From this result, as the time taken to change the topology differs depending on the speed at which the device moves, it can be said that more dominant forgetting factors are required when the device moves faster. The results show that a channel selection algorithm based on TOW dynamics with forgetting factors can effectively function in decentralized mobile IoT networks, where the network environment is highly variable.

VII. MASSIVE REAL SIMULATION

In this section, we perform simulations to evaluate the performance of the channel selection methods in each algorithm using the actual taxi mobility data in Tokyo, Japan, from January 2018 to April 2018 [36]. This dataset periodically records the GPS positions of taxis with an interval of 30 seconds. We evaluate the performance of distributed channel selection based on each method by using the mobility data of 300 taxis around Tokyo Station (1km×1km) as shown Fig. 20. We also use the simulation parameters shown in Table 3 and use the FSR for the entire network as the evaluation index. The FSR results of each method are shown in Fig. 21. Furthermore, the forgetting factors α and β in TOW dynamics are set to 0.95 and 0.98, respectively.

Fig. 21 shows that the channel selection method based on TOW dynamics with forgetting factors has the highest FSR compared to the other methods in a massive-scale real environment. Therefore, we conclude that the channel selection method based on TOW dynamics, including forgetting factors, works well in the real environment of decentralized networks.

VIII. CONCLUSION

Owing to the increase in the number of IoT devices belonging to wireless networks and the limitation of frequency resources, the degradation of the communication quality caused by channel congestion is one of the most pressing problems faced by developers of IoT technology. Considering the hardware and software complexity limitations of IoT devices in fully decentralized networks, a sophisticated distributed channel selection algorithm is vital. The MAB algorithm for solving the MAB problem involves simple reinforcement learning, and it can be applied to channel selection algorithms.

Motivated by these backgrounds, this paper proposed a distributed channel selection method based on TOW dynamics, a simple and efficient MAB algorithm for decentralized IoT networks. Through implementation and experiments, we demonstrated the effectiveness of the proposed method in an actual wireless environment. In addition, we conducted simulation evaluations in a massive wireless environment. The experimental and simulation results showed that the communication quality could be improved by introducing forgetting factors into the TOW dynamics when IoT devices are densely deployed and the available channels change due to channel states and device movement. The proposed method shows higher accuracy in all scenarios than other methods, and the accuracy degradation is reduced even in more complex environments. In future work, we will explore how to set the optimal parameters by considering communication frequency and changes in the surrounding environment, such as the mobility of devices. In addition, we will extend the algorithm to more complicated systems, such as multi-hop networks.

REFERENCES

[1] Y.-C. Hsiao, M.-H. Wu, and S. C. Li, ‘‘Elevated performance of the smart city—A case study of the IoT by innovation mode,’’ *IEEE Trans. Eng. Manag.*, vol. 68, no. 5, pp. 1461–1475, Oct. 2021.

[2] Y. A. Qadri, A. Nauman, Y. B. Zikria, A. V. Vasilakos, and S. W. Kim, ‘‘The future of healthcare Internet of Things: A survey of emerging technologies,’’ *IEEE Commun. Surveys Tuts.*, vol. 22, no. 2, pp. 1121–1167, 2nd Quart., 2020.

[3] M. S. Farooq, S. Riaz, A. Abid, K. Abid, and M. A. Naeem, ‘‘A survey on the role of IoT in agriculture for the implementation of smart farming,’’ *IEEE Access*, vol. 7, pp. 156237–156271, 2019.

[4] *Information and Communication White Paper*, Ministry of Internal Affairs and Communications, Tokyo, Japan, 2020, pp. 76–77.

[5] A. Al-Fuqaha, M. Guizani, M. Mohammadi, M. Aledhari, and M. Ayyash, ‘‘Internet of Things: A survey on enabling technologies, protocols, and applications,’’ *IEEE Commun. Surveys Tuts.*, vol. 17, no. 4, pp. 2347–2376, 4th Quart., 2015.

[6] Y. Sun, H. Song, A. J. Jara, and R. Bie, ‘‘Internet of Things and big data analytics for smart and connected communities,’’ *IEEE Access*, vol. 4, pp. 766–773, 2016.

[7] G. A. Akpakwu, B. J. Silva, G. P. Hancke, and A. M. Abu-Mahfouz, ‘‘A survey on 5G networks for the Internet of Things: Communication technologies and challenges,’’ *IEEE Access*, vol. 6, pp. 3619–3647, 2018.

[8] M. Chincoli, P. den Boef, and A. Liotta, ‘‘Cognitive channel selection for wireless sensor communications,’’ in *Proc. IEEE 14th Int. Conf. Netw., Sens. Control (ICNSC)*, May 2017, pp. 795–800.

[9] V. Kotsiou, G. Z. Papadopoulos, P. Chatzimisios, and F. Theoleyre, ‘‘Adaptive multi-channel offset assignment for reliable IEEE 802.15.4 TSCH networks,’’ in *Proc. Global Inf. Infrastruct. Netw. Symp. (GIIS)*, Oct. 2018, pp. 1–5.

[10] Z. Qin, G. Denker, C. Giannelli, P. Bellavista, and N. Venkatasubramanian, ‘‘A software defined networking architecture for the Internet-of-Things,’’ in *Proc. IEEE Netw. Oper. Manage. Symp. (NOMS)*, May 2014, pp. 1–9.

[11] F. Tang, Z. M. Fadlullah, B. Mao, and N. Kato, ‘‘An intelligent traffic load prediction-based adaptive channel assignment algorithm in SDN-IoT: A deep learning approach,’’ *IEEE Internet Things J.*, vol. 5, no. 6, pp. 5141–5154, Dec. 2018.

[12] V. Kotsiou, G. Z. Papadopoulos, D. Zorbas P. Chatzimisios, and A. F. Theoleyre, ‘‘Blacklisting-based channel hopping approaches in low-power and lossy networks,’’ *IEEE Commun. Mag.*, vol. 57, no. 2, pp. 48–53, Feb. 2019.

[13] Bluetooth SIG. *Bluetooth Specification Version 5.3*. Accessed: Jan. 1, 2022. [Online]. Available: https://www.bluetooth.com/specifications/specs/core-specification/

[14] R. Tanbourgi, J. P. Elsner, H. Jakel, and F. K. Jondral, ‘‘Adaptive frequency hopping in ad hoc networks with Rayleigh fading and imperfect sensing,’’ *IEEE Wireless Commun. Lett.*, vol. 1, no. 3, pp. 185–188, Jun. 2012.

[15] H. Ye, G. Y. Li, and B.-H. F. Juang, ‘‘Deep reinforcement learning based resource allocation for V2V communications,’’ *IEEE Trans. Veh. Technol.*, vol. 68, no. 4, pp. 3163–3173, Apr. 2019.

[16] X. Zhang, M. Peng, S. Yan, and Y. Sun, ‘‘Deep-reinforcement-learning-based mode selection and resource allocation for cellular V2X communications,’’ *IEEE Internet Things J.*, vol. 7, no. 7, pp. 6380–6391, Jul. 2020.

[17] L. Lai, H. Jiang, and H. V. Poor, ‘‘Medium access in cognitive radio networks: A competitive multi-armed bandit framework,’’ in *Proc. 42nd Asilomar Conf. Signals, Syst. Comput.*, Oct. 2008, pp. 98–102.

[18] L. Lai, H. El Gamal, H. Jiang, and H. V. Poor, ‘‘Cognitive medium access: Exploration, exploitation, and competition,’’ *IEEE Trans. Mobile Comput.*, vol. 10, no. 2, pp. 239–253, Feb. 2011.

[19] A. Baid, S. Mathur, I. Seskar, S. Paul, A. Das, and D. Raychaudhuri, ‘‘Spectrum MRI: Towards diagnosis of multi-radio interference in the unlicensed band,’’ in *Proc. IEEE Wireless Commun. Netw. Conf.*, Mar. 2011, pp. 534–539.

[20] H. Robbins, ‘‘Some aspects of the sequential design of experiments,’’ *Bull. Amer. Math. Soc.*, vol. 58, no. 5, pp. 527–535, 1952.

[21] R. Sutton and A. Barto, *Reinforcement Learning: An Introduction*. Cambridge, MA, USA: MIT Press, 1998.

[22] T. L. Lai and H. Robbins, ‘‘Asymptotically efficient adaptive allocation rules,’’ *Adv. Appl. Math.*, vol. 6, no. 1, pp. 4–22, Mar. 1985.

[23] P. Auer, N. Cesa-Bianchi, and P. Fischer, ‘‘Finite-time analysis of the multiarmed bandit problem,’’ *Mach. Learn.*, vol. 47, no. 2, pp. 235–256, 2002.

[24] S.-J. Kim, M. Aono, and E. Nameda, ‘‘Efficient decision-making by volume-conserving physical object,’’ *New J. Phys.*, vol. 17, no. 8, Aug. 2015, Art. no. 083023.

[25] S.-J. Kim, M. Aono, and M. Hara, ‘‘Tug-of-war model for the two-bandit problem: Nonlocally-correlated parallel exploration via resource conservation,’’ *Biosystems*, vol. 101, no. 1, pp. 29–36, Jul. 2010.

[26] S.-J. Kim, T. Tsuruoka, T. Hasegawa, M. Aono, K. Terabe, and M. Aono, ‘‘Decision maker based on atomic switches,’’ *AIMS Mater. Sci.*, vol. 3, no. 1, pp. 245–259, 2016.

[27] S.-J. Kim, M. Naruse, and M. Aono, ‘‘Harnessing the computational power of fluids for optimization of collective decision making,’’ *Philosophies*, vol. 1, no. 3, pp. 245–260, Dec. 2016.

[28] S.-J. Kim and M. Aono, ‘‘Amoeba-inspired algorithm for cognitive medium access,’’ *Nonlinear Theory Appl., IEICE*, vol. 5, no. 2, pp. 198–209, 2014.

[29] K. Kuroda, H. Kato, S.-J. Kim, M. Naruse, and M. Hasegawa, ‘‘Improving throughput using multi-armed bandit algorithm for wireless LANs,’’ *Nonlinear Theory Appl., IEICE*, vol. 9, no. 1, pp. 74–81, 2018.

[30] J. Ma, S. Hasegawa, S.-J. Kim, and M. Hasegawa, ‘‘A reinforcement-learning-based distributed resource selection algorithm for massive IoT,’’ *Appl. Sci.*, vol. 9, no. 18, p. 3730, Sep. 2019.

[31] S. Hasegawa, R. Kitagawa, T. Ito, T. Nakajima, S.-J. Kim, Y. Shoji, and M. Hasegawa, ‘‘Performance evaluation of machine learning based channel selection algorithm implemented on IoT sensor devices and its application to wireless sensor network for building monitoring system,’’ in *Proc. Int. Conf. Artif. Intell. Inf. Commun. (ICAIIC)*, Feb. 2020, pp. 161–166.

[32] *LAPIS Semiconductor, Lazurite920mhz(Q504H) Datasheet, LAPIS Shinyokohama*. Japan. Accessed: 2010. [Online]. Available: https://www.lapis-tech.com/lazurite-jp/products/lazurite-pi-gateway

[33] *The Network Simulator; Ns-3*. Accessed: Aug. 1, 2021. [Online]. Available: https://www.nsnam.org/

[34] A. Zear, P. K. Singh, and Y. Singh, ‘‘Intelligent transport system: A progressive review,’’ *Indian J. Sci. Technol.*, vol. 9, no. 32, pp. 1–8, Aug. 2016.

[35] W. B. Qaim, A. Ometov, A. Molinaro, I. Lener, C. Campolo, E. S. Lohan, and J. Nurmi, ‘‘Towards energy efficiency in the internet of wearable things: A systematic review,’’ *IEEE Access*, vol. 8, pp. 175412–175435, 2020.

[36] W. Liu, K. Nakauchi, and Y. Shoji, ‘‘A neighbor-based probabilistic broadcast protocol for data dissemination in mobile IoT networks,’’ *IEEE Access*, vol. 6, pp. 12260–12268, 2018.

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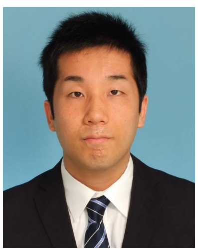

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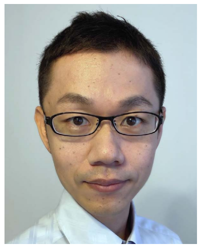

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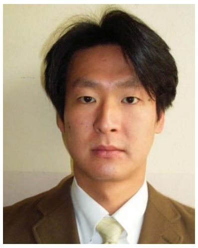

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