IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 1 November 2023, accepted 13 December 2023, date of publication 21 December 2023,
date of current version 28 December 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3345831

RESEARCH ARTICLE

Dynamic Slot Allocation Without Explicit Request Messages for Wireless Sensor Networks With Limited Resources

JONGKWAN LEE[1] AND MINWOO LEE[2], (Member, IEEE)
[1]Department of Computer Science, Korea Military Academy, Seoul 01805, South Korea
[2]Department of Maritime AI and Security, Korea Maritime and Ocean University, Busan 49112, South Korea

Corresponding author: Minwoo Lee (iminu@kmou.ac.kr)

This work was supported by the Hwarang-dae Research Institute of Korea Military Academy.

ABSTRACT This paper presents a novel dynamic slot allocation algorithm for wireless sensor networks designed to overcome resource constraints. Our algorithm operates without explicit request messages and adapts the transmission period and data transmission amount according to changes in the monitored environment. As such, it addresses the challenge of allocating wireless resources efficiently and fairly while considering packet drop rate, transmission delay, channel status, and transmission opportunities. However, networks with limited resources can only collect and process some of the necessary information for optimal allocation. Therefore, our proposed scheme uses accumulative information on allocated resources instead of additional overhead information. Our algorithm outperforms the reservation-based resource allocation scheme in conditions where packet arrival rates change dynamically, which achieves over 15% improvement in terms of network throughput, indicating its suitability for networks operating under constrained resources.

INDEX TERMS Dynamic resource allocation, wireless network, limited resources, request message, overhead.

I. INTRODUCTION

Wireless Sensor Networks (WSNs) are spatially distributed sensor nodes connected via wireless communication for data collection and transmission to fulfill specific tasks [1], [2], [3]. These nodes are small, low-power devices with one or more sensors for data collection, a microcontroller for data processing, and a wireless transceiver for communication. Sensors' decreasing cost and size have led to the denser deployment of nodes, expanding monitoring range, and improving sensing accuracy. The Internet of Things (IoT) has rapidly advanced related technologies, such as sensing, communication, computation, and caching, leading to widespread usage of WSNs across various application fields, such as health care, environmental monitoring, smart farming, robotics, smart cities, military, among others [4], [5], [6], [7], [8].

The associate editor coordinating the review of this manuscript and approving it for publication was Cesar Vargas-Rosales.

WSNs encounter a broad range of challenges related to energy efficiency, security, scalability, reliability, and quality of service [9], [10], [11]. One of the primary concerns is the limited bandwidth available for communication, which poses difficulties in transmitting significant amounts of data at high rates. Additionally, WSNs often operate in environments with multiple wireless networks, leading to interference and impacting the network's performance [12], [13]. The problem of limited bandwidth becomes more acute with increased sensor nodes sharing radio resources in the mutual interference range.

In WSNs, sensor nodes are deployed locally and responsible for monitoring their respective areas. Consequently, local changes can only be detected by some sensors, resulting in some sensors having data to transmit while others do not. Additionally, the amount of sensing data to transmit varies, depending on the monitoring target. Therefore, a static allocation of wireless resources and an identical allocation strategy for each node is inappropriate, reducing network throughput [14]. It is necessary to allocate wireless resources dynamically to sensors with data to transmit in dense WSNs to improve network throughput. The unpredictable and non-periodic nature of sensing data has led to the inherent limitations of static resource allocation in WSNs, driving the development of dynamic resource allocation schemes.

Wireless resources can be allocated dynamically based on multiple criteria, such as energy, latency, fairness, and throughput, depending on the intended purpose of using the network. However, allocating resources that consider multiple criteria can result in complex algorithms that require collecting additional information from the sensors to operate. This additional information can lead to an increase in overhead, reducing the payload throughput of the network. The impact of this overhead on resource allocation must be addressed, especially in networks with limited wireless resources [15], [16].

In recent years, there has been growing interest in utilizing artificial intelligence (AI) to develop dynamic resource allocation algorithms [17]. However, the effectiveness of machine learning methods for this task depends on the quality and quantity of data used for training. In cases where data is scarce or inadequately representative of the problem domain, model performance may suffer. Furthermore, if network conditions or data distributions change over time, the model may become obsolete and unable to adapt to the new conditions. As a result, resource allocation strategies based on machine learning approaches may not be suitable for dynamic network environments.

We propose a novel dynamic slot allocation scheme for WSNs based on time division multiple access (TDMA) that eliminates the need for explicit information exchange among nodes. Unlike conventional schemes that require slot demand information from neighboring nodes to allocate slots to specific nodes, our proposed scheme enables nodes to transmit data without requiring dedicated wireless resources to send slot demand information to neighboring nodes. This allows more payload data to be transmitted, improving network throughput. Additionally, the proposed scheme is suitable for real-time applications by dynamically allocating slots according to traffic demand.

The significant contributions of this study include the following:

- We propose a dynamic slot allocation scheme for TDMA-based WSNs, which does not require any request messages that incur overhead costs.
- We show through mathematical analysis that the overhead costs are not negligible in WSNs with insufficient bandwidth.
- The proposed scheme is validated through simulations under various dynamic and static traffic conditions.

The rest of this paper is organized as follows. In Section II, we review existing studies on dynamic slot allocation in wireless networks. Section III presents the system model proposed in this paper, while Section IV describes the proposed system in detail. Section V shows a performance analysis of the proposed scheme by various simulations. Finally, we conclude this paper in Section VI.

II. RELATED WORKS

Several studies have investigated algorithms for dynamically allocating wireless resources. In conventional dynamic TDMA systems, each node requests slot allocation from its neighboring nodes during a dedicated period, specifying the number and priority of slots needed. The slots are then assigned to nodes according to their requested priority. However, this approach creates an unfairness issue if a node repeatedly requests slot allocation with a high priority. To address this problem, Ting et al. proposed a modification that considers the number of priorities and the number of slots requested. The algorithm requires sharing request information with all nodes, resulting in significant overheads. Hence, it may not be suitable for networks with limited resources.

In [18], the authors proposed an algorithm that dynamically adjusts timeslot length to maximize network capacity based on the bit error rate (BER). Their approach outperforms static TDMA regarding packet loss rate, particularly in low BER scenarios. However, the authors did not provide details on calculating the BER or how nodes reach a consensus on the adjusted slot length. In other words, the algorithm needs an overhead analysis. Each node listens to the channel and collects data from 1-hop neighbors to obtain slot allocation information. The nodes then combine this data to generate node neighborhood information (NNI), transmitted periodically within a specific frame. Upon receiving the NNI, a node updates its own NNI based on the information received from neighboring nodes. However, the proposed algorithm generates significant overhead because it allocates a separate period within the frame to exchange NNIs.

In [19], the authors proposed a dynamic slot allocation scheme that leverages idle slots of neighboring nodes to retransmit failed packets and improve network throughput. The scheme takes advantage of the broadcasting nature of wireless transmission, where the source node and its neighbors can detect transmission failures based on packet acknowledgments from the destination node. If a node has been assigned a slot but has no data to transmit, it temporarily returns it, enabling other nodes to use the idle slot for packet retransmission. Compared to static TDMA and other cooperative TDMA schemes, this approach enhances network throughput, especially in densely deployed networks with poor channel conditions. However, to exploit idle slots cooperatively, the scheme requires a control period consisting of as many mini-slots as nodes in the network, resulting in substantial overhead.

The reviewed studies have demonstrated outstanding performance by dynamically allocating slots by exchanging additional data or control packets with neighboring nodes. Nonetheless, the issue of reducing the significant overhead still needs to be solved.

In [20], the authors presented a machine learning-based approach for wireless resource management that involves a deep neural network (DNN) to learn a given optimization algorithm. The DNN approximates the optimization algorithm by using the algorithm's results as target values for the DNN model. Optimization algorithms typically require computationally expensive operations involving multiple iterations, such as matrix inversion, singular value decomposition (SVD), and bi-section. In contrast, the proposed approach employs a learned DNN model that only requires simple operations such as matrix-vector multiplication, leading to a significant reduction in computation compared to the optimization algorithm. The authors demonstrated, through simulations, that the proposed approach approximates the widely used minimization of the weighted mean-square error (WMMSE) algorithm for power control problems [21]. However, the performance of the proposed approach may not surpass that of the given optimization algorithm since the DNN model is only an approximation of WMMSE. Furthermore, as a data-driven method, obtaining adequate training data is crucial. The quality and quantity of training data mainly influence the performance of the DNN model. However, obtaining a balanced dataset covering diverse network conditions is impractical and time-consuming. Additionally, wireless networks are dynamic rather than static, with network topology, traffic type, and QoS varying over time.

A continuous learning framework for wireless resource allocation in a dynamic environment was investigated to address the issue of obtaining sufficient and balanced training data [22], [23]. The proposed method selects data samples that relatively degrade system performance on a dataset collected within static network conditions and uses them as training data for DNN model learning. The assumption is that the model learned from the worst-case data would perform well for the rest of the data, enabling incremental adaptation to a dynamic environment. The performance of the proposed framework has been validated through simulations of various wireless resource problems and has shown the potential to extend to other related issues. However, assuming an episodically static environment over time is not practical in the real world. Much computational cost is required for continuous learning, making it unsuitable for nodes with limited resources.

In [24], the authors presented a novel distributed block-based Q-learning algorithm for slot allocation in clustered IoT networks. The primary objective of the proposed algorithm is to mitigate inter- and intra-cluster interference and enhance the Signal to Interference Ratio (SIR). The controller responsible for forming and advertising the slot schedule utilizes the Q-learning algorithm to learn interference between clusters and selects a time block based on the Q-value updated by the received SIR. The algorithm then allocates timeslots with acceptable SIR levels to the nodes. IoT networks can converge to a collision-free transmission in static network conditions with the proposed approach.

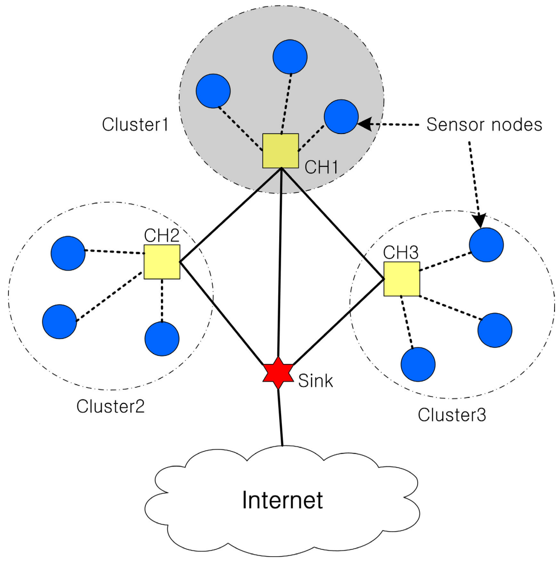

FIGURE 1. System model.

In [25], Yang et al. proposed the BrainIOT scheme to solve the resource demand issue in the Industrial Internet of Things (IIoT). The scheme conducts resource reservations based on predicted future service, which achieves 96% accuracy. The BrainIOT scheme improves the performance of delay, blocking probability, and resource utilization.

Since machine learning is primarily a data-driven approach, obtaining comprehensive data similar to the current network state is critical to achieving optimal performance. However, it may not be practical in dynamic networks.

III. SYSTEM MODEL

This study investigates infrastructure-less wireless networks comprising multiple sensor nodes, cluster header nodes, and a sink node. Our system model is illustrated in Fig. 1. Each cluster consists of numerous sensor nodes and a single cluster header node. Both the clusters and sink nodes are organized as separate networks. Within a cluster, sensors only communicate with their corresponding cluster header node and not with adjacent sensor nodes. Our main focus is on solving the resource allocation problem in the context of intra-cluster networks.

In intra-cluster networks, two distinct types of nodes exist: cluster header and sensor nodes. We denote the cluster header node as CH and N sensor nodes as S_n, $n \in (1, 2, \ldots, N)$. The header node, which is considerably more potent than the sensor nodes and connected to them within a one-hop distance, is responsible for gathering the data from the sensor nodes. The sensor nodes, which possess limited resources, monitor the environment within a specific region and transmit the corresponding sensory data to the header node. These sensor nodes are equipped with a buffer capable of dynamically storing generated sensory data resulting from environmental fluctuations. The older packets are sequentially removed if a packet size exceeds the buffer's capacity.

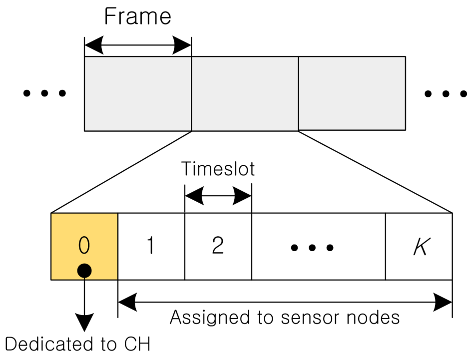

FIGURE 2. Frame structure.

A reservation-based approach allocates timeslots for packet transmission to the nodes. The structure of the transmission frame is depicted in Fig. 2, composed of $K+1$ timeslots. We denote the timeslot as $T_k, k \in (0, 1, 2, \ldots, K)$. The frames are periodically repeated until the network is terminated. The first timeslot in each frame, designated as T_0, is reserved for the header node, which transmits control data crucial for network management and operation. The remaining timeslots, excluding the first timeslot, can be dynamically assigned to different sensor nodes for each frame based on the respective traffic load of each sensor node.

In our study, we have established two assumptions concerning timeslot allocations. The first assumption is that the cluster header node can solely receive sensory data from a single sensor node during each timeslot, precluding the assignment of two or more sensor nodes to the same timeslot. The second assumption is that each sensor node is assigned a maximum of one timeslot for each frame because the number of sensor nodes is significantly higher than the number of slots in the frame.

As a result, the following equations must be satisfied.

$$\sum_{k=1}^{K} \theta_{s_n}^{(k)} \leq 1, n \in (1, 2, \ldots, N) \tag{1}$$

$$\sum_{n=1}^{N} \theta_{s_n}^{(k)} \leq 1, k \in (1, 2, \ldots, K) \tag{2}$$

$$\sum_{k=1}^{K} \sum_{n=1}^{N} \theta_{s_n}^{(k)} = K \tag{3}$$

where $\theta_{s_n}^{(k)} \in 0, 1$ is a binary indicator to denote whether a sensor node, S_n, is assigned to timeslot k.

IV. THE PROPOSED SCHEME

This chapter presents a detailed description of the proposed scheme for dynamically allocating slots in wireless sensor networks. Table 1 presents the notations used in this paper and their respective meanings.

A. OVERVIEW OF THE PROPOSED SCHEME

The flowchart of the proposed scheme is illustrated in Fig. 3, which comprises two modules: 1) a slot allocation module

TABLE 1. The list of symbols and notations used in this paper.

Notation	Meaning
CH	cluster header node
S_n	sensor nodes, $n \in \{1, 2, ..., N\}$
SAI	slot allocation information
N	number of sensor nodes in a cluster
K	number of timeslot in a frame.
B	buffer size of a node
$\mathbb{P}_j$	a set of S_n assigned a slot in the j^{th} frame.
$\mathbb{N}_j$	a set of S_n that do not assigned a slot in the j^{th} frame.
α	utilization factor for S_ns that are included in the $\mathbb{P}$ and transmit data successfully
β	utilization factor for S_ns that are included in the $\mathbb{P}$ and transmit data unsuccessfully
γ	utilization factor for S_ns that are included in the $\mathbb{N}$
η	discount factor
$u(S_n^{(j)})$	utilization of S_n in the j^{th} frame
$AU(S_n)$	accumulated utilization of S_n
$rank(S_n^{(j)})$	ranking of S_n in descending order based on the value of AU in the j^{th} frame

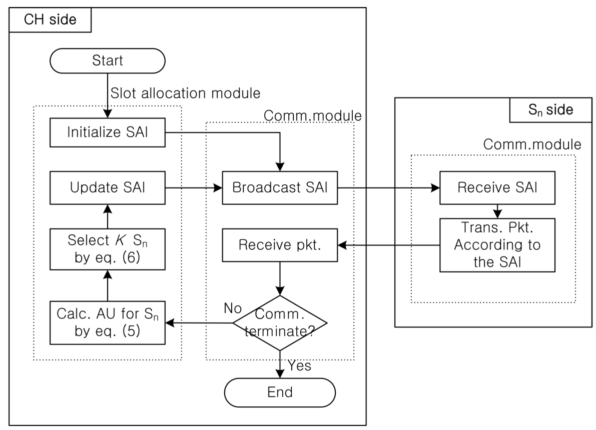

FIGURE 3. Block diagram for the proposed scheme.

and 2) a communication module. The CH node calculates the accumulated slot utilization for each sensor node and updates the slot allocation information (SAI) in the slot allocation module. The SAI contains information on the slots allocated to each sensor node. It is important to note that the slot allocation module operates solely on the CH node, and the sensor nodes do not participate in SAI updates. In the communication module, the CH node and sensor nodes communicate with each other using a TDMA approach. The CH node transmits the updated SAI, obtained from the slot allocation module, to the sensor nodes and receives data from the sensor nodes assigned the respective timeslots. The sensor nodes, in turn, receive the updated SAI from the CH node and transmit their data during the designated timeslot. If no data is in the buffer, the sensor node will not transmit data, implying that the allocated slot is not utilized.

The operation procedure of the proposed scheme can be divided into five steps as followings.

- The first step is to generate the SAI randomly. To minimize the overhead, the CH does not collect explicit information from sensor nodes, such as buffer status or channel conditions. Therefore, timeslots are randomly allocated to sensor nodes in the initial stage of network operation.

- The second step involves calculating the accumulated slot utilization for each sensor node with the previous M slot utilization.
- The third step is to update the SAI based on the accumulated slot utilization calculated in the second step.
- The fourth step is to transmit the updated SAI to the sensor nodes.
- The fifth step is that the sensor node to which the time slot is assigned by the updated SAI transmits data.

The process then repeats from the second step to the fifth step until the network ends

B. SLOT ALLOCATION MODULE

We denote that $\mathbb{P}^{(j)}$ and $\mathbb{N}^{(j)}$ is a set of sensor nodes assigned a slot and is a set of sensor nodes that do not assign to a slot in a j^{th} frame, respectively. It should be noted that all sensor nodes are classified as elements of either set $\mathbb{P}$ or $\mathbb{N}$ based on the SAI.

There are three cases to calculate slot utilization for a node.

- Case 1: a sensor node is assigned a timeslot, i.e., $S_n \in \mathbb{P}$, and transmits data from the timeslot successfully.
- Case 2: a sensor node is assigned a timeslot, i.e., $S_n \in \mathbb{P}$, and cannot transmit data from the timeslot for any reason.
- Case 3: a sensor node is not assigned a timeslot, i.e. $S_n \in \mathbb{N}$.

Slot utilization of a sensor node in j^{th} frame, $u(S_n^{(j)})$ is α, β, and γ for each case as follows:

$$u(S_n^{(j)}) = \begin{cases} \alpha & \text{if } S_n \in \mathbb{P}_j \text{ and successful transmission} \\ \beta & \text{if } S_n \in \mathbb{P}_j \text{ and unsuccessful transmission} \\ \gamma & \text{otherwise} \end{cases} \tag{4}$$

In addition, we define accumulative slot utilization(AU) of S_n in frame j as follows:

$$AU(S_n^{(j)}) = \sum_{m=1}^{M} \eta^{m-1} u(S_n^{(j-m+1)}), \tag{5}$$

where M is the number of previous frames used to calculate the AU and η is the discount factor, of which the value is between 0 and 1. The larger M, the more past $u(S_n)$ is applied to calculate the $AU(S_n)$. It should be noted that only $u(S_n)$s for the current frame and the M-1 past frames are used. The larger the η, the greater the weight of the past $u(S_n)$. If the η is zero, then the past $u(S_n)$s are ignored, and if η is one, both current and past $u(S_n)$s are used in the same weight to calculate $AU(S_n)$.

Each sensor node becomes an element of either $\mathbb{P}^{(j+1)}$ or $\mathbb{N}^{(j+1)}$ as follows:

$$S_n \in \begin{cases} \mathbb{P}^{(j+1)} & \text{if } rank(S_n^{(j)}) \leq K, n \in \{1, 2, ..N\} \\ \mathbb{N}^{(j+1)} & \text{otherwise} \end{cases} \tag{6}$$

where the $rank(S_n^{(j)})$ is the ranking of S_n in descending order based on the value of AU in the j^{th} frame.

Our proposed scheme allocates timeslots exclusively to sensor nodes that belong to the set $\mathbb{P}$. The slot allocation process is straightforward, with timeslots assigned to sensor nodes in order of their $rank(S_n)$. Specifically, the first timeslot for a sensor node, T_1, is allocated to a sensor node with a rank of 1, and the last timeslot, the K^{th} timeslot, is assigned to a sensor node with a rank of K. The CH node updates the SAI using the equation presented in Eq. (7).

$$\theta_{S_n}^{(k)} = \begin{cases} 1 & \text{if } S_n \in \mathbb{P} \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

where k=$rank(S_n)$.

C. COMMUNICATION MODULE

The CH node and sensor nodes communicate using a TDMA protocol in the communication module. During each frame, the CH transmits SAI to the sensor nodes during a dedicated timeslot, T_0 and receives packets from the sensor nodes during the remaining timeslots. The SAI is updated in the slot allocation module based on information about the sensor node that sent the packets that the CH successfully received.

Sensor nodes have three operation modes: transmitting, listening and sleeping. Sensor nodes remain in sleep mode to conserve energy except for the dedicated slot for CH and the timeslot allocated to them. The sensor node transitions to listening mode to receive the SAI from the CH during the dedicated slot. If the sensor node has a timeslot allocated by the SAI and a packet to transmit in the buffer, it switches to transmitting mode during the timeslot. However, if there is no packet to transmit, even if the sensor node has a slot allocated, it remains in sleep mode. Additionally, sensor nodes can transmit packets only to the CH because other nodes are in sleep mode during the transmitting mode.

V. PERFORMANCE ANALYSIS

In this section, we present an experimental analysis of the performance of three schemes, including the conventional TDMA that allocates slots in a fixed manner, dynamic TDMA (DTDMA) that only considers slot utilization information in the previous frame [26], and the proposed method. Three metrics are utilized to evaluate the scheme: normalized system throughput, system packet drop rate (PDR), and Jain's fairness index for the PDR of each node. Normalized system throughput is defined as the ratio of packets transmitted to the CH to the number of packets generated from all sensor nodes. System PDR is defined as the ratio of dropped packets due to buffer overflow to the number of packets generated from all sensor nodes. Jain's fairness index is used to assess the fairness of PDR distribution among sensor nodes.

The packets transmitted by a sensor node are generated using a Poisson distribution with the parameter λ. To analyze the performance of the proposed scheme, we conduct simulations in two types of networks: homogeneous and

TABLE 2. Parameter values used for simulation.

Parameter	Values
K	5
N	100
B	5, 10, 15, 20, 25, 30, 35, 40, 45, 50
α	1
β	0
γ	0.5, 1, 1.5, 2
η	0.9

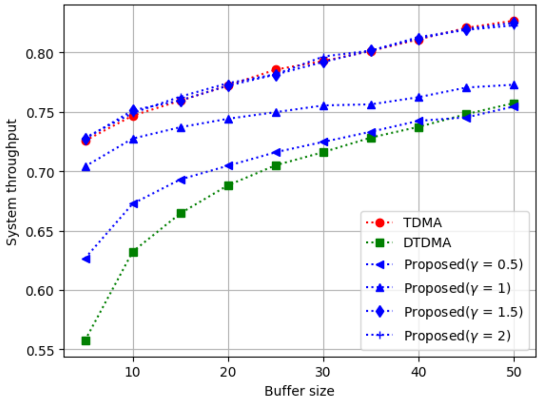

FIGURE 4. Throughput according to buffer size in a homogeneous network: α = 1, β = 0, η=0.9.

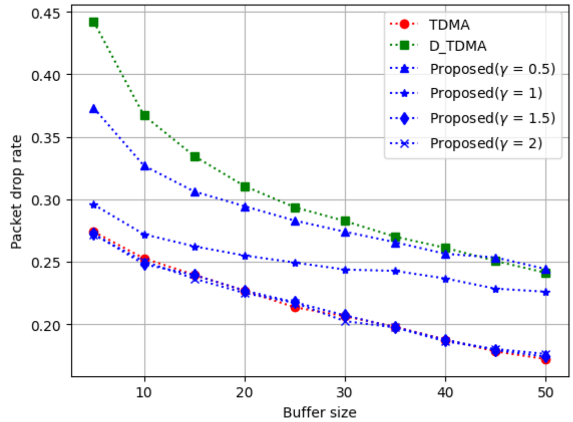

FIGURE 5. PDR according to buffer size in a homogeneous network: α = 1, β = 0, η=0.9.

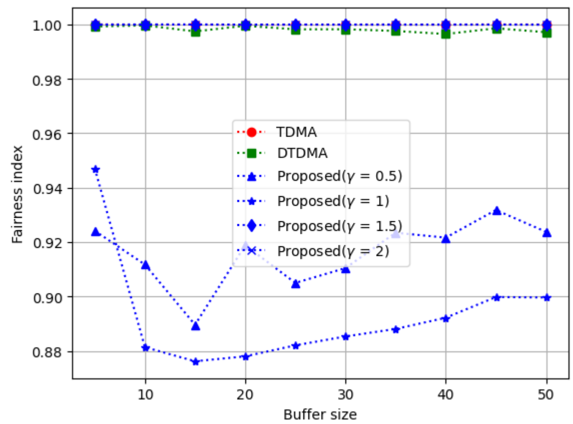

FIGURE 6. Fairness index according to buffer size in a homogeneous network: α = 1, β = 0, η=0.9.

heterogeneous. In a homogeneous network, all sensor nodes have the same λ value that changes over time. Conversely, in a heterogeneous network, each sensor node has a different λ value that changes over time, meaning they have different λ values at specific times. The parameter values utilized in the simulations are presented in Table 2.

A. PERFORMANCE IN HOMOGENEOUS NETWORKS

1) SYSTEM THROUGHPUT

Fig. 4 represents the system throughput for different buffer sizes in the three schemes. The buffer size increases incrementally from 5 to 50. Under the same traffic conditions, the blue line represents the proposed scheme when α=1, β=0, and η=0.9, and the red line represents TDMA.

Since all nodes have the same packet generation rate, the optimal slot allocation method is to allocate slots equally to all nodes in a TDMA manner. Therefore, as observed from Fig. 4, the proposed scheme using γ=1.5 or γ=2 and TDMA exhibit the best performance. The proposed scheme using a large γ compared to α performs similarly to TDMA. As explained earlier, when γ is greater than α in the proposed scheme, nodes without a slot are likely to be allocated a slot in the subsequent frame. Thus, the proposed scheme using a large γ and TDMA exhibit similar performance in terms of throughput. Meanwhile, DTDMA showed the worst performance. It is because DTDMA reacts too sensitively to the slot state information of the previous frame, unnecessarily making slot allocation different for each node.

2) SYSTEM PDR

Fig. 5 represents the PDR for different buffer sizes in the three schemes. As the buffer size increases, the PDR decreases in both schemes. Similar to the system throughput performance, the proposed scheme employing γ=1.5 or γ=2 and conventional TDMA exhibit the best PDR performance.

3) FAIRNESS

Fig. 6 represents the fairness index of each node's PDR for different buffer sizes in the three schemes. As TDMA allocates slots equally to nodes with the same λ, its fairness index is close to 1. Similarly, the proposed scheme using γ = 1.5 or γ = 2.0 operates similarly to TDMA, resulting in a fairness index close to 1. Although the fairness of DTDMA is less than TDMA, it is mostly close to 1. However, the proposed scheme using γ = 0.5 and γ = 1.0 exhibits a lower fairness index. This indicates that the proposed scheme does not allocate slots equally to nodes even when they have the same λ. This is because when γ is lower than α, nodes that have successfully transmitted packets with allocated slots in the past frame tend to be allocated slots continually in the next frame.

The simulation results demonstrate that the proposed scheme, with appropriate parameters, performs similarly to TDMA, which is considered the best method in a homogeneous network.

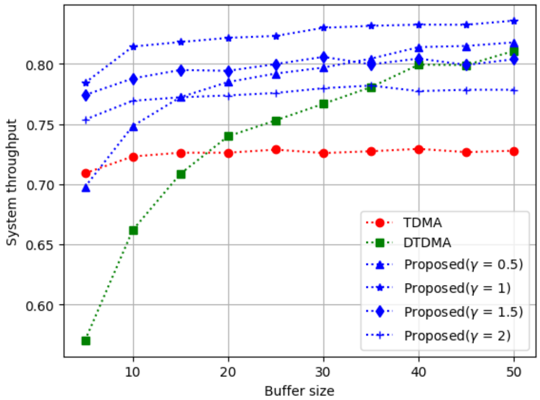

FIGURE 7. Throughput according to buffer size in a heterogeneous network: $\alpha = 1$, $\beta = 0$, η=0.9.

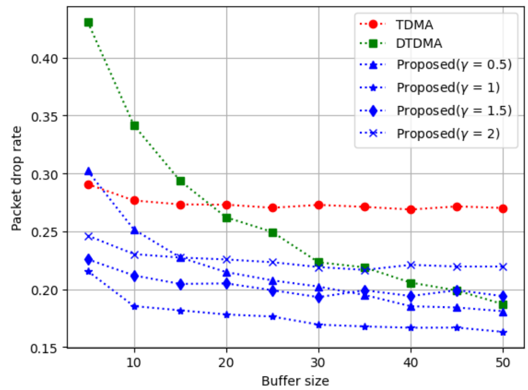

FIGURE 8. PDR according to buffer size in a heterogeneous network: $\alpha = 1$, $\beta = 0$, η=0.9.

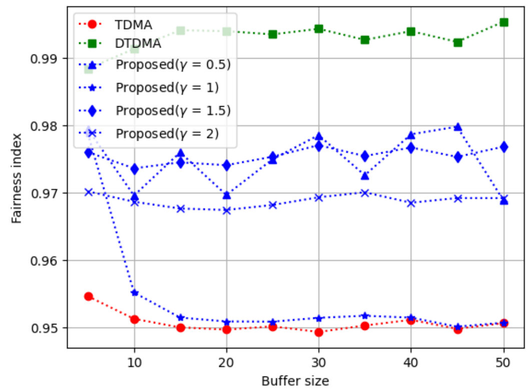

FIGURE 9. Fairness index according to buffer size in a heterogeneous network: $\alpha = 1$, $\beta = 0$, η=0.9.

B. PERFORMANCE IN HETEROGENEOUS NETWORKS

1) SYSTEM THROUGHPUT

Fig. 7 represents the system throughput for different buffer sizes for three schemes in heterogeneous networks comprising sensor nodes with different λs. All the schemes exhibit an increase in system throughput as the buffer size grows. Nevertheless, the proposed scheme outperforms TDMA in terms of system throughput. TDMA allocates slots uniformly to all nodes regardless of their λ, leading to insufficient slot allocation for nodes with a high number of packets and unnecessary allocation of many slots to nodes with fewer packets to transmit. In contrast, the proposed scheme favors allocating slots to nodes with a larger λ over those with a smaller λ, resulting in better performance in heterogeneous networks composed of nodes with varying λ. Meanwhile, DTDMA shows the lowest performance when the buffer size is less than 20, but since it can dynamically allocate slots, it performs better than TDMA when the buffer size is 20 or more. However, the performance of DTDMA does not reach that of the proposed scheme. This means that the performance of dynamic slot allocation in DTDMA is not better than the proposed scheme.

The proposed scheme demonstrates the best performance when γ is equal to 1, but its performance deteriorates when γ exceeds 1. This is due to the proposed scheme's behavior being similar to TDMA when γ is significantly larger than α. TDMA and the proposed scheme using a different γ can achieve high throughput if the sensor node has a large buffer. However, they are unsuitable for heterogeneous networks consisting of sensor nodes with small buffers.

2) SYSTEM PDR

Fig. 8 represents the system PDR for different buffer sizes in the three schemes in heterogeneous networks. As the buffer size increases, all the schems exhibit a decline in system PDR. Nevertheless, the proposed schemes perform considerably better than TDMA and DTDMA. Notably, the proposed scheme attains the best performance when γ equals 1, reaching the lowest system PDR at the smallest buffer size. Similarly to the simulation results for system throughput, the proposed scheme employing an unsuitable γ requires a substantial buffer size to achieve a low PDR.

3) FAIRNESS

Fig. 9 represents the fairness index for each node's PDR for different buffer sizes in the three schemes in a heterogeneous network. The fairness index for all the schemes is relatively high, reaching 0.95 or higher. When γ equals 1 in the proposed scheme, it exhibits the lowest fairness index, which is almost identical to TDMA. This indicates that the proposed scheme handles packets from nodes with a large λ better than those from nodes with a small λ. However, the difference is negligible since the fairness index is 0.95.

The simulation results affirm that the proposed scheme with suitable parameters outperforms TDMA and DTDMA in a heterogeneous network.

C. EFFECT OF OVERHEAD COSTS

We distinguish between two types of data: payload data and overhead data. Payload data refers to the primary information about the object to be sensed, while overhead data refers to auxiliary data utilized for the slot allocation process. It is assumed that one timeslot is needed to transmit both payload and overhead data.

To evaluate the performance of TDMA systems, we utilize the M/D/1 model [27], [28]. We analyze the effect of overhead by comparing the existing scheme that uses overhead for

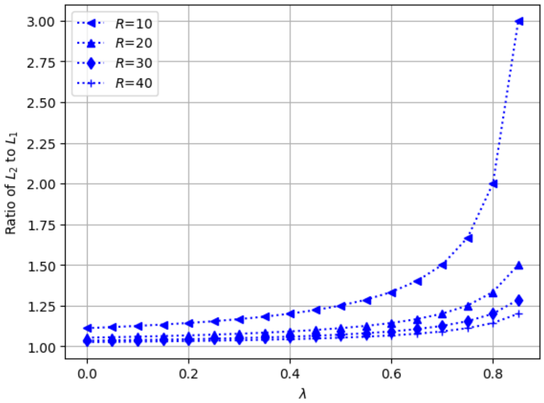

FIGURE 10. Ratio of L_2 to L_1 according to varying λ and R.

dynamic slot allocation and the proposed scheme that does not use it. To ensure a fair comparison, we assume that the frame structure, the number of timeslots per frame, and the length of the timeslots are all equal. In the existing scheme, each node transmits overhead data every R frame. On the other hand, in the proposed scheme, no overhead data is transmitted, and all slots are used for transmitting payload data. Consequently, if the service rate of the proposed scheme is one, the service rate of the existing scheme is $(R-1)/R$.

Then, the average number of payload data in the system for the existing scheme (L_1) and the proposed scheme (L_2) can be calculated as follows:

$$L_1 = \frac{R\lambda}{R(1-\lambda)-1}, \tag{8}$$

$$L_2 = \frac{\lambda}{1-\lambda} \tag{9}$$

Fig. 10 represents the ratio of L_2 to L_1 under varying values of λ and R. A higher ratio indicates that the existing scheme cannot transmit payload data at a faster rate than the proposed scheme. The results indicate that the ratio is insignificant when the value of λ is small or R is large. However, the ratio significantly increases as λ increases or R decreases. This implies that the effect of overhead becomes more pronounced as λ increases or R decreases. Notably, a large R is unsuitable for dynamic networks as updating the overhead data may not be fast enough. Hence, R cannot be set to a large value. In addition, as the cost of sensors continues to decline, sensor nodes are densely deployed, leading to an inevitable increase in λ. Therefore, the proposed scheme is more appropriate than the existing scheme for dynamic WSNs.

D. EFFECT OF REWARDS AND DISCOUNT FACTOR

In the proposed scheme, it is recommended that β be smaller than both α and γ since there is no need to continuously allocate slots to nodes that are unable to transmit packets during the allocated slots.

The priority given to the slot allocation of each node is determined by the ratio of α to γ. When this ratio (i.e., $\frac{\alpha}{\gamma}$) exceeds 1, nodes that have successfully transmitted packets during the previous frame's allocated slots will likely receive slot allocation again in the next frame. Conversely, when the ratio is less than 1, nodes that lack a slot are more likely to receive an allocation in the next frame.

Meanwhile, when β is smaller than both α and γ, nodes that fail to transmit with the allocated slot will have to wait for a longer duration until the slots are reallocated to them. In addition, η determines the extent to which each node's slot utilization in the past frame is considered in the slot allocation for the next frame. As the value of η approaches 1, the past frame's slot utilization is more heavily weighted, whereas as it approaches 0, it has less impact.

E. ENERGY EFFICIENCY

The sensor nodes operate in one of three modes: transmission, reception, and silence. The energy consumption during the transmission mode is relatively high compared to reception and silence mode. In silent mode, sensor nodes are idle and do not actively participate in the networks. Therefore, the energy consumption is relatively low. In reception mode, where the sensor node actively listens for incoming data, the node consumes more energy than in silent mode but less than during transmitting.

We analyze the proposed scheme regarding energy consumption by comparing it with conventional TDMA and control message-based dynamic TDMA schemes [18], [19], [29], [30]. In conventional TDMA, slot allocation information is predefined and remains fixed until network termination. Thus, sensor nodes operate in silence mode in all slots except those allocated for data transmission. Although the conventional TDMA has inefficient slot utilization, as we verified in the above simulation results, it is the most energy-efficient. In control message-based dynamic TDMA, sensor nodes exchange control messages to CH for dynamic slot allocation. Thus, the sensor nodes require additional periods for reception and transmission modes compared to static TDMA. This results in more energy consumption.

Meanwhile, the proposed scheme does not require the transmission of any control messages, so it is more energy-efficient than control message-based dynamic TDMA. However, the proposed scheme also receives slot allocation information from CH. Thus, it can not be more energy efficient than conventional TDMA. As a result, the proposed scheme consumes more energy than conventional TDMA but less than control message-based dynamic TDMA.

VI. CONCLUSION

We present a dynamic slot allocation scheme without transmission of explicit request messages that can cause substantial overhead, particularly in wireless networks with limited resources. The proposed scheme dynamically allocates slots based on slot utilization calculated by the slot allocation information and packet transmission results for each node in the previous frame. As a result, it assigns more slots to nodes with a greater number of packets in the buffer and fewer slots to nodes with fewer packets. We evaluated the proposed scheme through computer simulations for homogeneous and heterogeneous networks. In the homogeneous network, the proposed scheme demonstrated comparable performance to TDMA, which is the best-performing scheme. However, in the heterogeneous network, the proposed scheme outperformed TDMA and DTDMA significantly. Additionally, we verified that the proposed scheme performs well even with small buffer sizes. Therefore, the proposed scheme is suitable for homogeneous and heterogeneous networks consisting of nodes with constrained resources.

REFERENCES

[1] I. F. Akyildiz, W. Su, Y. Sankarasubramaniam, and E. Cayirci, "A survey on sensor networks," *IEEE Commun. Mag.*, vol. 40, no. 8, pp. 102–114, Aug. 2002.

[2] J. Sarangapani, *Wireless Ad Hoc and Sensor Networks: Protocols, Performance, and Control*. Boca Raton, FL, USA: CRC Press, 2017.

[3] J. Yick, B. Mukherjee, and D. Ghosal, "Wireless sensor network survey," *Comput. Netw.*, vol. 52, no. 12, pp. 2292–2330, Aug. 2008.

[4] L. Cui and X. Xie, *Wireless Sensor Networks*. Singapore: Springer, 2021.

[5] B. Rashid and M. H. Rehmani, "Applications of wireless sensor networks for urban areas: A survey," *J. Netw. Comput. Appl.*, vol. 60, pp. 192–219, Jan. 2016.

[6] D. Kandris, C. Nakas, D. Vomvas, and G. Koulouras, "Applications of wireless sensor networks: An up-to-date survey," *Appl. Syst. Innov.*, vol. 3, no. 1, p. 14, Feb. 2020.

[7] M. P. Đurišić, Z. Tafa, G. Dimić, and V. Milutinović, "A survey of military applications of wireless sensor networks," in *Proc. Medit. Conf. Embedded Comput. (MECO)*, Jun. 2012, pp. 196–199.

[8] A. Gaur, B. Scotney, G. Parr, and S. McClean, "Smart city architecture and its applications based on IoT," *Proc. Comput. Sci.*, vol. 52, pp. 1089–1094, Jan. 2015.

[9] B. Bhushan and G. Sahoo, "Requirements, protocols, and security challenges in wireless sensor networks: An industrial perspective," in *Handbook of Computer Networks and Cyber Security: Principles and Paradigms*. Cham, Switzerland: Springer, 2020, pp. 683–713. [Online]. Available: https://doi.org/10.1007/978-3-030-22277-2_27

[10] D. S. Ibrahim, A. F. Mahdi, and Q. M. Yas, "Challenges and issues for wireless sensor networks: A survey," *J. Global Sci. Res.*, vol. 6, no. 1, pp. 1079–1097, 2021.

[11] N. R. Patel and S. Kumar, "Wireless sensor networks' challenges and future prospects," in *Proc. Int. Conf. Syst. Model. Advancement Res. Trends (SMART)*, Nov. 2018, pp. 60–65.

[12] X. Huan, K. S. Kim, S. Lee, E. G. Lim, and A. Marshall, "A beaconless asymmetric energy-efficient time synchronization scheme for resource-constrained multi-hop wireless sensor networks," *IEEE Trans. Commun.*, vol. 68, no. 3, pp. 1716–1730, Mar. 2020.

[13] J. Liu, Z. Zhao, J. Ji, and M. Hu, "Research and application of wireless sensor network technology in power transmission and distribution system," *Intell. Converged Netw.*, vol. 1, no. 2, pp. 199–220, Sep. 2020.

[14] S. Bhandari and S. Moh, "A MAC protocol with dynamic allocation of time slots based on traffic priority in wireless body area networks," *Int. J. Comput. Netw. Commun.*, vol. 11, no. 4, pp. 25–41, Jul. 2019.

[15] M. A. Mahmood, W. K. G. Seah, and I. Welch, "Reliability in wireless sensor networks: A survey and challenges ahead," *Comput. Netw.*, vol. 79, pp. 166–187, Mar. 2015.

[16] N. Tamura and H. Yomo, "Low-overhead wake-up control for wireless sensor networks employing wake-up receivers," *IEICE Trans. Commun.*, vol. E102.B, no. 4, pp. 732–740, 2019.

[17] M. S. Frikha, S. M. Gammar, A. Lahmadi, and L. Andrey, "Reinforcement and deep reinforcement learning for wireless Internet of Things: A survey," *Comput. Commun.*, vol. 178, pp. 98–113, Oct. 2021. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0140366421002681

[18] K. Cao, C. Dong, and F. Yu, "Dynamic time-slot allocation algorithm based on environment sensing in wireless sensor network," in *Proc. IEEE 4th Int. Conf. Signal Image Process. (ICSIP)*, Jul. 2019, pp. 490–494.

[19] J.-K. Lee, H.-J. Noh, and J. Lim, "A cooperative TDMA MAC protocol using dynamic slot assignment scheme," in *Proc. Int. Conf. Inf. Netw. (ICOIN)*, Jan. 2013, pp. 216–220.

[20] H. Sun, X. Chen, Q. Shi, M. Hong, X. Fu, and N. D. Sidiropoulos, "Learning to optimize: Training deep neural networks for interference management," *IEEE Trans. Signal Process.*, vol. 66, no. 20, pp. 5438–5453, Oct. 2018.

[21] Q. Shi, M. Razaviyayn, Z.-Q. Luo, and C. He, "An iteratively weighted MMSE approach to distributed sum-utility maximization for a MIMO interfering broadcast channel," *IEEE Trans. Signal Process.*, vol. 59, no. 9, pp. 4331–4340, Sep. 2011.

[22] H. Sun, W. Pu, M. Zhu, X. Fu, T.-H. Chang, and M. Hong, "Learning to continuously optimize wireless resource in episodically dynamic environment," in *Proc. IEEE Int. Conf. Acoust., Speech Signal Process. (ICASSP)*, Jun. 2021, pp. 4945–4949.

[23] H. Sun, W. Pu, X. Fu, T.-H. Chang, and M. Hong, "Learning to continuously optimize wireless resource in a dynamic environment: A bilevel optimization perspective," *IEEE Trans. Signal Process.*, vol. 70, pp. 1900–1917, 2022.

[24] F. Hussain, R. Hussain, A. Anpalagan, and A. Benslimane, "A new block-based reinforcement learning approach for distributed resource allocation in clustered IoT networks," *IEEE Trans. Veh. Technol.*, vol. 69, no. 3, pp. 2891–2904, Mar. 2020.

[25] H. Yang, J. Yuan, C. Li, G. Zhao, Z. Sun, Q. Yao, B. Bao, A. V. Vasilakos, and J. Zhang, "BrainIoT: Brain-like productive services provisioning with federated learning in industrial IoT," *IEEE Internet Things J.*, vol. 9, no. 3, pp. 2014–2024, Feb. 2022.

[26] C. Benrebbouh and L. Louail, "Dynamic TDMA for wireless sensor networks," in *Proc. 30th Wireless Opt. Commun. Conf. (WOCC)*, Oct. 2021, pp. 204–208.

[27] J.-K. Lee, "Performance analysis of dynamic TDMA and fixed TDMA in tactical data link," *J. Korea Inst. Mil. Sci. Technol.*, vol. 21, no. 4, pp. 489–496, 2018.

[28] M. U. Thomas, "Queueing systems. Volume 1: Theory (Leonard Kleinrock)," *SIAM Rev.*, vol. 18, no. 3, pp. 512–514, Jul. 1976.

[29] C. Lin, X. Cai, Y. Su, P. Ni, and H. Shi, "A dynamic slot assignment algorithm of TDMA for the distribution class protocol using node neighborhood information," in *Proc. 11th IEEE Int. Conf. Anti-Counterfeiting, Secur., Identificat. (ASID)*, Oct. 2017, pp. 138–141.

[30] T. Yin, Y. Wang, M. Zhao, and J. Xiao, "A modified dynamic TDMA slot allocation algorithm in ad hoc network," in *Proc. 1st IEEE Int. Conf. Comput. Commun. Internet (ICCCI)*, Oct. 2016, pp. 124–128.

JONGKWAN LEE received the B.S. degree in electronic engineering from Korea Military Academy, Seoul, South Korea, in 2000, the M.S. degree in electronic engineering from the Korea Advanced Institute of Science and Technology (KAIST), Daejeon, South Korea, in 2004, and the Ph.D. degree in network-centric warfare (NCW) engineering from Ajou University, Suwon, South Korea, in 2014.

He has been a Military Officer, since 2000, and is currently an active Army Officer, a Lieutenant Colonel of the Republic of Korea (ROK) Army. From 2011 to 2014, he participated with the Tactical Network Research Center, Ajou University. He is currently an Associate Professor with the Department of Computer Science, Korea Military Academy. His research interests include tactical wireless networks, cyber warfare, and artificial intelligence and their applications.

MINWOO LEE (Member, IEEE) received the B.S. degree in aero telecommunication and information engineering from Korea Aerospace University, Goyang, South Korea, in 1998, and the Ph.D. degree in network-centric warfare (NCW) engineering from Ajou University, Suwon, South Korea, in 2013. He is currently a Faculty Member with the Department of Maritime Artificial Intelligence and Security, Korea Maritime and Ocean University, and teaches networking and cybersecurity courses for graduate and undergraduate students. He served as a Naval Officer for more than 20 years, a Team Leader of the Cyber Technology Research Team with the Cyber Command of ROK, and a Technical Researcher with the Naval Jang Bogo-III Cooperation Group. His research interests include LEO satellite networks, network security, and cyber-electronic warfare.