Ad Hoc Networks 135 (2022) 102936

Contents lists available at ScienceDirect

Ad Hoc Networks

journal homepage: www.elsevier.com/locate/adhoc

Survey paper

A survey on analytical models for dynamic resource management in wireless body area networks

Beom-Su Kim [a], Babar Shah [b], Ting He [c], Ki-Il Kim [a,*]

[a] Department of Computer Science and Engineering, Chungnum National University, Daejeon 34134, Republic of Korea
[b] College of Technological Innovation, Zayed University, Abu Dhabi, United Arab Emirates
[c] Department of Computer Science and Engineering, Pennsylvania State University, State College 16801, United States of America

ARTICLE INFO

Keywords:
Resource optimization
Theoretical analysis
Adaptive decision-making
Medium access control (MAC)
Resource constraints
Body shadowing
Heterogeneous traffic flow
Inter-WBAN interference

ABSTRACT

Compared with typical wireless sensor networks, wireless body area networks (WBANs) have distinct features: on-body communication, a large amount of interference, and dynamic topology changes caused by gestures. Accordingly, the resource management algorithm in the medium access control (MAC) protocol should be dynamic, adaptive, and energy-efficient. Hence, recent studies tend to optimize the available resources by applying several types of analytical models. Although these models have been categorized in terms of their objectives, the major differences between their methodologies have not been emphasized and discussed. In this study, we classify the analytical models applicable to dynamic resource management, and clarify their characteristics and use cases. We present the basic principles, approach classification, comparison, and guidance for dynamic resource management, and investigate state-of-the-art resource management techniques according to the corresponding analytical models. Furthermore, research challenges on dynamic resource management in WBAN are identified to facilitate future research in this area.

1. Introduction

A wireless body area network (WBAN) is a special network designed for in-body and on-body communication. In WBANs, sensors are attached to the surface of or inside the body and wirelessly transmit the collected data to a coordinator. IEEE 802.15.6 [1] is an international wireless communication standard for WBANs and supports in-body and on-body communication models. Its purpose is to support differentiated quality of service (QoS) for urgent traffic, and efficiently use the limited available resources owing to sensor size. Accordingly, the IEEE 802.15.6 task group established the first draft of the requirements for WBAN applications [2]. The technical requirements of WBANs are as follows:

(a) A WBAN typically supports link throughput up to tens of kbps. Low data rates of less than 300 kbps are expected in medical applications [3]; however, non-medical applications require data rates of up to 10 Mbps. (b) The packet error rate (PER) should be less than 10% for a 256-octet payload under a dynamic network condition in which the user is constantly moving. (c) Reliability, latency, and jitter should be supported for WBAN applications. For non-medical applications, latency should be less than 250 ms, and jitter should be less than 50 ms. However, medical applications require a latency of less than 125 ms. (d) The application lifetime should be extended from 24 h to several years through self-management [4]. Power management should cover the duty cycle from 0.1% or less to higher values.

To satisfy these requirements, appropriate resource allocation should be performed at the medium access control (MAC) layer [5]. However, the resource management schemes specified in the IEEE 802.15.6 standard are not effective in a dynamic WBAN environment [6]. For example, frequent body movements cause channel fading [7], leading to loss of important data or waste of resources owing to retransmission. That is, the dynamic environment generated by body movements is a major consideration in the design of a WBAN. In addition, a WBAN consists of heterogeneous nodes with different QoS requirements [8]. This implies that in adaptive resource allocation, various traffic patterns, data priorities, and data rates should be considered. Moreover, the transmission ranges between adjacent WBANs can overlap in public areas, and thus inter-WBAN interference may occur [9]. As a result, a predefined access time or static output power may cause mutual interference with adjacent WBANs.

1.1. Motivation

Several types of dynamic resource management schemes have been proposed to address the major challenges in WBANs. Dynamic

* Corresponding author.
E-mail address: kikim@cnu.ac.kr (K.-I. Kim).

https://doi.org/10.1016/j.adhoc.2022.102936
Received 11 January 2022; Received in revised form 25 May 2022; Accepted 3 July 2022
Available online 8 July 2022

resource management can be regarded as the efficient use of limited resources; however, it implies energy saving, reliability, and QoS improvement [8]. To achieve these objectives, existing resource management schemes adaptively optimize the target parameters according to the current network conditions. Most of them manage the available resources through dynamic link scheduling or dynamic transmission power control. However, in addition to the main benefits of optimizing quantitative resources, such as output power and radio resources, additional gains can be obtained by dynamically adjusting MAC parameters, such as wake-up interval, backoff bound, and data rate [5]. To maximize these gains, it is important to determine the target parameters after the configuration of a specific network scenario where performance fluctuations occur. Another important consideration for effective resource management is to determine a balance point between various factors, such as complexity, energy consumption, and reliability, rather than optimizing a single objective [10]. For example, reliability and energy efficiency can be improved through transmission power control. However, as the output power should be increased to improve reliability, increasing reliability and extending network lifetime are conflicting objectives. Therefore, it is important to adaptively optimize a target parameter considering the trade-off between multiple objectives.

Unfortunately, owing to the dynamic nature of WBANs, it is quite difficult to determine the optimal resource allocation policy and achieve a trade-off between multiple factors [6]. To resolve this, several types of analytical models have been applied to dynamic resource management techniques. Analytical models allow flexible decision-making for resource allocation in a variety of situations. Recent studies model existing WBAN problems using an appropriate analytical model and determine the optimal strategies for efficient resource management. However, some analytical models are not suitable for a WBAN environment, or they can only be applied to a specific WBAN scenario given various factors, such as adaptability, complexity, and automation. That is, if we understand the characteristics of analytical models and their use cases, it is possible to develop an optimal resource management strategy according to network conditions. In this study, we classify analytical models applicable to dynamic resource management in WBANs, and clarify their characteristics and use cases. In addition, we present the basic principles, approach classification, comparison, and guidance for dynamic resource management, and investigate state-of-the-art resource management techniques based on these models.

Recently, MAC protocols have been categorized in terms their objectives and operations. Common issues in WBANs are described in [11–13]. MAC-specific issues such as reliability and fault tolerance are covered in [14,15]. Common issues in MAC protocols, such as energy efficiency, security, and coexistence, were addressed in [16–20]. Dynamic resource management techniques were first investigated in [21], but the focus was only on the transmission power control mechanism. In contrast, we explore various types of dynamic resource management techniques and analyze the effectiveness of the corresponding analytical models. In addition, we review all relevant research directions rather than focus on a single functional goal, such as energy efficiency, reliability, or differentiated QoS with terminology given in (Table 1).

1.2. Contributions

The main contributions of this study are summarized below.

- We introduce challenging issues in WBANs and explain the importance of dynamic resource management.
- We describe dynamic WBAN scenarios with performance fluctuations, and clarify the target parameters that should be optimized.
- We classify analytical models applicable to dynamic resource management in WBANs, and clarify their characteristics and use cases.
- We provide the basic principles, approach classification, comparison, and guidance for dynamic resource management, and categorize state-of-the-art resource management techniques according to the corresponding analytical models.
- We identify open research challenges on dynamic resource management in WBAN.

Table 1
List of acronyms.

WBAN	Wireless Body Area Network
QoS	Quality of Service
PER	Packet Error Rate
MAC	Medium Access Control
LOS	Line of Sight
NLOS	Non-Line of Sight
EMG	Electromyography
ECG	Electrocardiogram
EEG	Electroencephalography
CSMA/CA	Carrier Sense Multiple Access with Collision Avoidance
TPC	Transmission Power Control
EAP	Exclusive Access Phase
RAP	Random Access Phase
MAP	Managed Access Phase
ALOHA	Additive Links On-Line Hawaii Area
CM	Channel Model
SAR	Specific Absorption Rate
MCDM	Multi-Criteria Decision-Making
FLS	Fuzzy-Logic System
DRL	Deep Reinforcement Learning
MDP	Markov Decision Process
NN	Neural Network
TSR	Traffic Status Register
TDMA	Time-Division Multiple Access
RSSI	Received Signal Strength Indicator
SUI	Scheduled Upload Interval
CW	Contention Window
SW	Sliding Window
SINR	Signal-to-Interference and Noise Ratio
PLR	Packet Loss Rate
ACK	Acknowledgment
GA	Genetic Algorithm
PSO	Particle Swarm Optimization
ACO	Ant Colony Optimization
FPC	Fuzzy Power Controller
AHP	Analytic Hierarchy Process
PDR	Packet Delivery Ratio
BE	Backoff Exponent
NBS	Nash Bargaining Solution
RL	Reinforcement Learning
CNN	Convolutional Neural Network

1.3. Organization

The remainder of this paper is organized as follows. In Section 2, we discuss challenging issues in WBANs and the importance of dynamic resource management. In Section 3, we describe dynamic WBAN scenarios and clarify the target parameters that should be optimized. In Section 4, analytical models used for dynamic resource management are briefly described. In Section 5, we review state-of-the-art dynamic resource management schemes. Areas of future study and some concluding remarks are presented in Sections 6 and 7, respectively.

2. Challenges in resource management for WBANs

In WBANs, as sensor nodes are attached to the surface of or inside the human body, the channel condition changes dynamically according to the movement of the body [7]. User mobility causes channel fading between the coordinator and sensor nodes. The fading effect is time-variant, and the propagation condition depends on whether the sensor nodes are in the line of sight (LOS) of the coordinator or not (NLOS).

For example, assuming that the coordinator is located at the middle part of the body, a sensor node placed on the torso is always in LOS. By

Table 2
Different types of medical sensors.

Sensor type	Data rate	Bandwidth	Priority (0 to 7)
EMG	320 kbps	0–10000 Hz	6,7
ECG	288 kbps	100–1000 Hz	6,7
EEG	42.3 kbps	0–150 Hz	6,7
Glucose	1600 bps	0–50 Hz	4,5
Temperature	120 bps	0–1 Hz	0–3
Cochlear implant	100 kbps	–	0–3
Voice	50–100 kbps	–	0–3

contrast, a sensor node attached to the limb may be in NLOS, depending on body movements (e.g., walking and sitting). If radio resources are statically allocated to nodes, then energy and bandwidth may be wasted at some nodes owing to channel fading. That is, a static resource allocation scheme cannot adaptively respond to dynamic channel conditions. For this reason, the primary function of MAC protocols [15] in WBANs is to dynamically adjust MAC parameters, such as superframe length, number of dedicated time slots, and transmission power level, after the current body posture is recognized, or upcoming body movements are predicted. In addition, the mobility characteristics of the human body have been linked to the inherent limitations of WBANs, leading to the development of dynamic resource management techniques that are specifically designed for WBANs. In this section, we describe the unique characteristics of WBANs that should be considered along with on-body communication, and we introduce the types of dynamic resource management that are required in medical applications.

2.1. Heterogeneous traffic flow

According to the IEEE 802.15.6 standard, a WBAN includes one coordinator and a range of nodes between 1 and 64. Each node collects various personal data and transmits them to the coordinator. Table 2 shows important physiological parameters that can be monitored using the WBAN. To provide differentiated QoS for high-priority data (e.g., electromyography (EMG), electrocardiogram (ECG), and electroencephalography (EEG)), the coordinator should selectively allocate radio resources to each node according to data priorities [22]. The simplest way to support QoS for emergency or critical data is to allocate more dedicated time slots to critical nodes. However, as the on-body communication link exhibits significant fluctuation [7], a fixed channel allocation leads to performance degradation or resource waste.

Therefore, a priority-based resource allocation scheme [8] is generally considered in combination with the gait-cycle recognition method. That is, the time point with the best link quality is determined through the gait-cycle recognition method, and the coordinator allocates dedicated time slots to the critical node at the time point. Although the scheduled link allocation method can meet the strict requirements of each traffic (e.g., reliability and latency), resources may be wasted, depending on the channel conditions. Accordingly, most QoS mechanisms [5] tend to be studied with energy-aware mechanisms aimed at optimizing MAC parameters, such as retransmission count and packet drop threshold. To prevent inefficient use of superframe time, a dynamic superframe structure can also be used for handling heterogeneous traffic based on user priorities. In addition, it is possible to support differentiated QoS by improving the carrier sense multiple access with collision avoidance (CSMA/CA)-based channel contention mechanism. For example, the CSMA/CA-based MAC protocol can dynamically determine the backoff bounds to increase the probability of channel access for high-priority traffic.

2.2. Resource constraints

A WBAN is a wireless system consisting of ultra-small sensor devices that can be implanted into or worn on the human body to continuously or periodically monitor important physiological signs [22]. Owing to the nature of these sensors, their batteries are small and difficult to recharge [4]. Therefore, the MAC protocol should reduce unnecessary energy consumption to prolong the lifetime of WBANs. Energy conservation in WBANs can be achieved through dynamic resource management according to the current network condition.

For example, to prevent retransmission owing to transmission failure, a dynamic link-scheduling algorithm based on link-quality prediction can be used in WBANs. Likewise, a dynamic transmission power control (TPC) mechanism can be adopted to determine the optimal output power according to the specific condition of a WBAN. A dynamic radio sleep–wake schedule is also recommended for energy efficiency. That is, the duty cycle can be dynamically adjusted based on the traffic pattern so that overhearing and idle listening may be reduced. In addition, the data-relaying service is an effective option to save energy. The IEEE 802.15.6 standard is based on a one-hop star topology, but also supports a two-hop star topology extension to reduce transmission power. In the two-hop extension mode, a node can reduce transmission power by half so that a more efficient TPC may be possible. Thus, the node should dynamically select an appropriate transmission mode considering the current network topology.

2.3. Intra- and inter-WBAN interference

To alleviate the effect of packet collisions in intra-WBAN communication [9], the IEEE 802.15.6 standard adopts three access modes: beacon mode with superframes, non-beacon mode with superframes, and non-beacon mode without superframes. As illustrated in Fig. 1, the superframe structure is divided into the exclusive access phase (EAP), random access phase (RAP), and managed access phase (MAP). The EAP and RAP are random access intervals based on CSMA/CA or slotted additive links on-line Hawaii area (ALOHA). The EAP is used only for high-priority traffic, whereas the RAP is used for all types of traffic. The MAP is used to arrange unscheduled allocation intervals, scheduled allocation intervals, and improvised polling access intervals. Generally, MAC protocols based on IEEE 802.15.6 achieve differentiated QoS and energy saving by allocating appropriate access phases to each node according to the current network condition.

For example, a random access MAC protocol improves energy efficiency through a dynamic backoff scheme based on user priorities, whereas a scheduled-access MAC protocol supports differentiated QoS through dynamic link scheduling based on link quality. In addition, a hybrid MAC protocol using both access phases can be adopted to achieve differentiated QoS and energy-saving. This implies that the coordinator should dynamically arrange the access phases in a superframe, considering the current network conditions and traffic patterns.

In addition, in public facilities such as hospitals, inter-WBAN interference may occur owing to the overlapping transmission ranges of nearby WBANs. Thus, a mechanism for smooth coexistence with adjacent WBANs is important to avoid interference between WBANs. To mitigate inter-WBAN interference, dynamic channel selection and dynamic TPC are feasible solutions. For example, a coordinator can periodically change its operating channel by including the channel hopping state and next channel hop fields in the beacon frame.

3. Causes of dynamics in WBANs

As described earlier, various MAC parameters should be optimized to achieve differentiated QoS or energy saving. However, unpredictable network situations and inherent limitations of WBANs render decision-making difficult [6]. For efficient resource management, we should identify a specific network scenario in which performance degradation occurs, and then determine the target parameters (e.g., number of time slots and transmission power level). That is, available resources should be used as efficiently as possible by optimizing the target parameters. In this section, we introduce specific network scenarios that require dynamic resource management, and we clarify the corresponding target parameters.

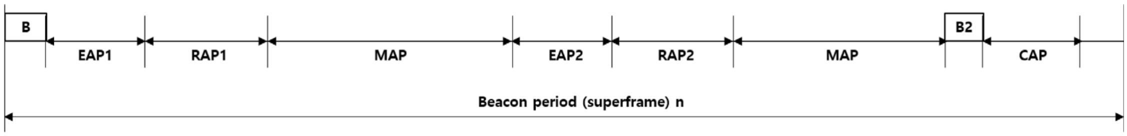


Fig. 1. Illustration of superframe structure.

Table 3
Channel modeling scenarios.

Scenario	Description	Frequency band	Channel model
S1	Implant to implant	402–405 (MICS) MHz	CM1
S2	Implant to body surface	402—405 (MICS) MHz	CM2
S3	Implant to external	402–405 (MICS) MHz	CM2
S4	Body surface to body surface (LOS)	400, 600, 900 MHz/2.4, 3.1–10.6. GHz	CM3
S5	Body surface to body surface (NLOS)	400, 600, 900 MHz/2.4, 3.1–10.6. GHz	CM3
S6	Body surface to external (LOS)	900 MHz/2.4, 3.1–10.6. GHz	CM4
S7	Body surface to external (NLOS)	900 MHz/2.4, 3.1–10.6. GHz	CM4

3.1. Frequent body movements

It is clear that regular mobility or any sport activity causes a high level of fluctuations in the received signal. It is claimed in [23] that, in the case of jogging, the variation of the received signal (waist-to-chest channel) is ± 15 dB; however, the variation of the received signal for a motionless user is ± 3 dB. That is, the coordinator requires detailed information regarding on-body channels for efficient resource management. For this purpose, human mobility models have been developed to recognize or classify human activities according to the quality of wireless links between sensor nodes, as well as a path-loss model that considers channel fading owing to body movements. Several factors, such as the radio frequency band, body characteristics, and surrounding environment, can be used as parameters of the path-loss model. According to the IEEE 802.15.6 standard, the path-loss model can be expressed as follows:

$$PL(d)_{dB} = PL_{d_0} + 10nlog_{10}\left(\frac{d}{d_0}\right) + X_\sigma, \tag{1}$$

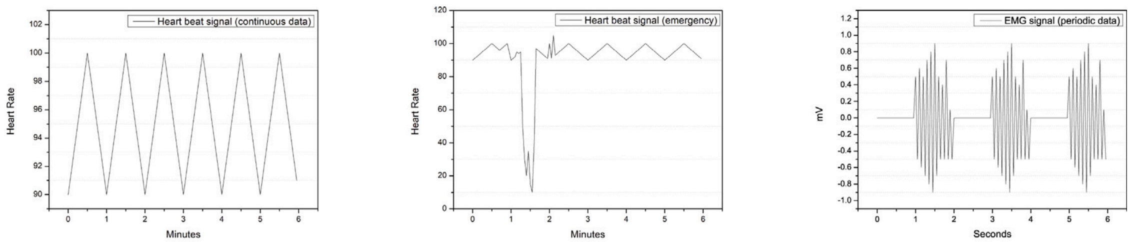
where PL_{d_0} denotes the path loss at a reference distance d_0, and n represents the path-loss exponent. The body-shadowing factor X_σ depends on body posture. However, the path-loss model for WBANs depends not only on the distance and shadowing component, but also on the frequency band. To develop a precise path-loss model for the available frequency band, the IEEE 802.15.6 working group derives scenarios based on the location of the communicating nodes. Subsequently, the scenarios are grouped using the channel model (CM), as shown in Table 3. The protocol designer should determine the appropriate CM according to the application. For example, the MAC protocol for body-surface-to-body-surface communication (scenarios S4 and S5) must apply the path-loss model for CM3. Further details on the measurement setup, derivation, and data analysis for each CM can be found in [24].

In addition, important features related to human mobility are discussed in [25]. The path-loss and human-mobility models are used to develop a dynamic resource allocation scheme capable of making adaptive decisions after recognizing the current body posture or gait cycle. For example, it may be the best decision for the coordinator to allocate radio resources at the peak point with the best link quality according to the gait cycle. However, when the link quality between the coordinator and the node is poor, it is advisable to postpone or abort the resource allocation. The target parameters that can be dynamically adjusted using the characteristics of body movements are as follows:

- **Number of time slots/time slot duration:** In beacon mode with superframes, the coordinator provides information on the appropriate number of time slots and slot duration to nodes through the beacon frame. To prevent transmission failure or retransmission owing to body shadowing, the coordinator must dynamically determine the appropriate number of time slots and time-slot duration based on the link quality measured from packets received in the previous beacon period.
- **Superframe length:** In WBANs with unstable channel conditions, a large number of data packets can be dropped owing to delay violations. In such a situation, retransmissions are likely to fail again. Increasing the number of retransmissions leads to additional resource usage. To address this, the coordinator dynamically determines the length of the random-access or the scheduled-access phase considering the current channel state and the deadline of pending data on the node.
- **Data frame length:** As energy consumption is inversely proportional to frame length, sensors can reduce energy consumption by choosing a larger frame length. However, longer frames are more prone to channel errors and packet loss. Therefore, it is necessary to dynamically determine the optimal frame length to minimize the probability of energy loss or packet error owing to body movements.
- **Bit rate:** High-fading environments can lead to inefficient use of available resources; thus, the decision on the next transmission bitrate must be dynamically adjusted according to the variable radio channel parameters or short-term PERs.
- **Transmission power:** The power required for successful transmission depends on the current body posture. To increase reliability, it is highly important to determine the minimum transmission power level required for successful transmission according to body posture. In addition, energy efficiency can be improved if the optimal transmission power is calculated by considering the distance between the coordinator and the node, and body shadowing.

3.2. Various traffic patterns

To maximize the reliability and lifetime of WBANs, the MAC protocol should eliminate packet collision, idle listening, and overhearing [26]. However, a WBAN consists of heterogeneous nodes with different traffic requirements. As shown in Table 2, WBAN applications vary in terms of priorities, data rates, and traffic patterns. Thus, the nodes should wake up or go into sleep mode depending on their transmission cycle. Accordingly, the coordinator should allocate radio resources to a node after recognizing the traffic pattern. However, as shown in Fig. 2, sensor nodes have different traffic patterns, such as sending data continuously or periodically, or sending data when a sudden event (e.g., heart attack) occurs. A heart rate sensor continuously collects the heart rate and transmits it to the coordinator, whereas an EMG sensor transmits data at regular intervals. In addition, all types of sensors can suddenly detect emergency data outside the safety level. This implies that the coordinator should dynamically determine the



(a) Continuous data (heart beat) (b) Abnormal data (heart beat) (c) Periodic data (EMG)

Fig. 2. Example of various traffic patterns.

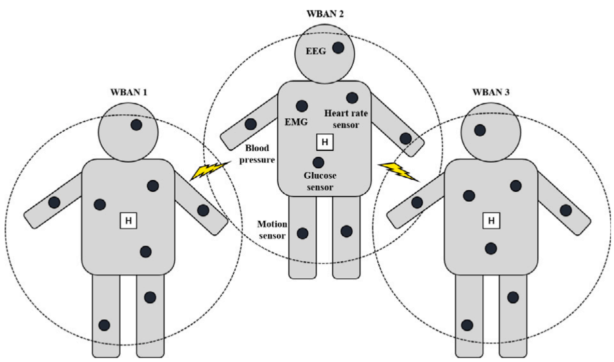


Fig. 3. Illustration of inter-WBAN interference.

access phase and number of time slots in the superframe, considering the traffic pattern and priority. The target parameters that can be dynamically adjusted using the traffic pattern are as follows.

- **Number of time slots/time slot duration:** More time slots can be placed in a superframe to meet the real-time demands of time-critical traffic. Thus, the coordinator should dynamically adjust the number of time slots and time-slot duration to adapt to traffic fluctuations.
- **Superframe length:** Longer superframes are used to reduce the energy consumed in transmitting and receiving redundant beacon frames. Accordingly, the coordinator can improve energy efficiency by dynamically adjusting superframe length based on traffic requirements and traffic patterns.
- **Backoff bounds:** In EAP, the backoff boundary can be dynamically adjusted to increase the probability of channel acquisition for nodes generating urgent or high-priority data.
- **Bit rate:** To support differentiated QoS, an efficient bitrate adaptation mechanism is required so that sensor bitrate may be adjusted according to the criticality of the data.

3.3. Coexistence of multiple WBANs

A practical problem is that multiple networks may coexist in a limited space with resource constraints. As shown in Fig. 3, in public facilities, channel interference between WBANs may occur owing to the overlapping transmission ranges of nearby WBANs [9]. To mitigate inter-WBAN interference, a centralized coordinator is required to control the output power and channel access. However, as a WBAN operates in a completely distributed manner, it does not have external information, such as frequency band, operating channel, scheduling policy, and output power of adjacent WBANs. As a result, the scheduling policy set to eliminate intra-WBAN interference causes significant channel interference between neighboring WBANs in the local network. In addition, static or predefined output power causes mutual interference with neighboring WBANs newly joined to the local network. Thus, a dynamic mechanism for smooth coexistence with adjacent BANs is important to avoid inter-WBAN interference. The target parameters that can be dynamically adjusted to mitigate inter-WBAN interference are as follows.

- **Number of time slots/time slot duration:** To share radio resources with neighboring WBANs, the coordinators explicitly exchange control messages to negotiate the number of time slots and time-slot duration.
- **Transmission power:** As the information on the identity of an active sensor in a specific time slot is private, the coordinator should dynamically adjust the transmission power without a time slot negotiation procedure to mitigate mutual channel interference.
- **Channel access order/operating channel:** Depending on the application, each WBAN may have different QoS requirements or even conflicting objectives. To support differentiated QoS for high-priority data, priority-based channel hopping should be performed by dynamically adjusting the operating channel and channel access order.
- **Superframe structure:** In a high-interference environment, the coordinator can adaptively change the superframe structure or superframe length based on the mutual interference degree to meet the QoS requirements.
- **Beacon period:** The coordinator can reduce potential allocation conflicts between adjacent WBANs by adjusting the beacon period that is not used in its neighbors.

4. Description of analytical models for dynamic resource management

In the previous section, we argued that specific dynamic network scenarios and target parameters should be determined to adaptively handle heterogeneous and ever-changing WBAN environments. Once the target parameters are determined, one out of several alternatives should be selected (e.g., operating channels), or parameter values should be calculated (e.g., transmission power level). Thus, the next step is to develop an optimization algorithm for determining the appropriate parameter values or alternatives. In this section, as shown in Fig. 4, we analyze the analytical models used for dynamic resource management and briefly describe their use cases and features.

4.1. Heuristic approach

In a nonlinear system such as a WBAN, a coordinator cannot make perfect decisions owing to time constraints and the lack of information. For example, channel allocation is an NP-hard problem in which an exact solution cannot be obtained in polynomial time. Heuristic approaches [27] are not aimed at obtaining an ideal solution but a fairly satisfactory answer. These approaches usually yield good results, but an inaccurate answer may randomly be obtained. In addition, heuristic algorithms usually have a reasonable execution time, but it cannot be logically proved that they are always correct. In WBANs, most dynamic resource allocation mechanisms do not explicitly state that they use

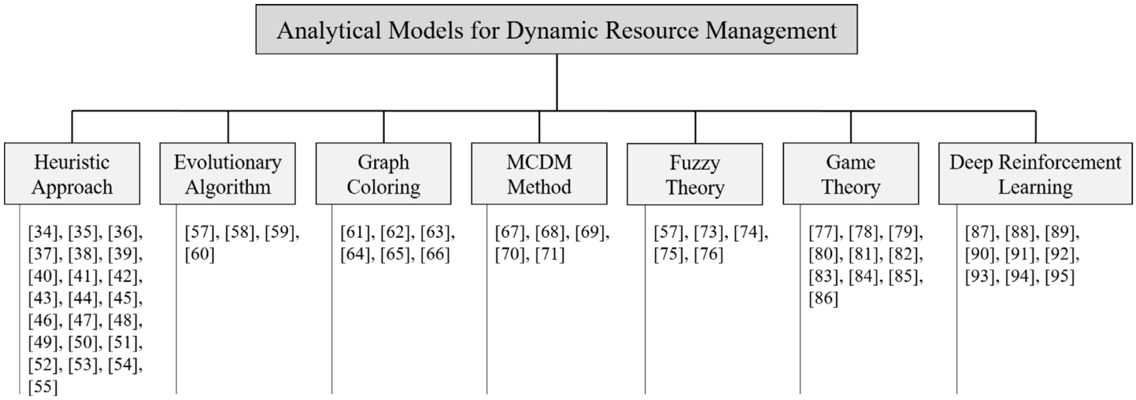


Fig. 4. Taxonomy of analytical models for WBANs.

a heuristic approach, but a number of techniques make probabilistic decisions based on historical data. Thus, when it is difficult to construct an analytic model owing to the nonlinear characteristics of WBANs, such as heterogeneous traffic patterns and on-body channel conditions, a heuristic approach can be an ideal solution to optimize target parameters.

4.2. Evolutionary algorithm (meta-heuristic approach)

A WBAN involves several optimization issues. For example, the rate at which the human body absorbs electromagnetic waves is called specific absorption rate (SAR), and is closely related to transmission power. When the SAR reaches a threshold, body temperature rises, causing tissue damage. In addition, the transmission power of a node should be optimized to mitigate the mutual interference between adjacent WBANs. That is, transmission power optimization is essential for successful transmission and prevention of side effects. In WBANs, evolutionary algorithms (i.e., meta-heuristics) [28] are primarily used to handle these optimization issues. An evolutionary algorithm lists candidate solutions and then gradually alters them to produce a sufficiently good solution. Here, a solution to the problem is called a gene, and the process of modifying these genes is expressed as evolution.

4.3. Graph coloring

In graph coloring [29], different colors are assigned to the vertices of a graph so that two adjacent vertices do not have the same color. The issue is to minimize the number of colors. The inter-WBAN interference problem can be modeled as a graph coloring problem. That is, different colors (e.g., channels) should be assigned to coexisting WBANs so that none of the WBANs with overlapping communication ranges have the same color. A coloring-based scheduling method that allocates different colors (i.e., time slots) to coexisting WBANs to avoid interference and increase the total throughput may also be considered.

4.4. Multi-criteria decision-making

The objective of multi-criteria decision-making (MCDM) [30] is to logically determine the weights between multiple metrics. It provides a ranking order of available alternatives according to the preferences of a decision-maker by logically defining the relationship between multiple metrics. That is, it facilitates decision-making in the presence of multiple criteria. In WBANs, MCDM is used to determine the weights between unrelated multiple metrics, such as buffer state, residual energy, and node position, so that an optimal relaying node may be selected. In addition, it is used to solve a selection problem (e.g., operating channel selection) by considering a multitude of decision factors, such as channel conditions, frame reception ratio, and latency. Similarly, the order of channel access can be determined by considering several determinants such as traffic type, priority, and QoS requirements.

4.5. Fuzzy theory

In fuzzy theory [31], an ambiguous state is expressed using verbal adjectives such as “very”, ”little”, and “slightly”. It is useful for cross-layer control of channel access because of its flexibility and simplicity. It is primarily used to overcome the channel uncertainty of WBANs, considering several factors such as channel conditions and QoS requirements. For example, when the coordinator considers the data and collision rate of each node to allocate a time slot, the terms “low”, ”medium”, and “high” are used to describe each metric, and these terms are considered input values. A typical fuzzy-logic system (FLS) normalizes the linguistic values of inputs and outputs in the range from 0 to 1. Then, the target parameter value (e.g., the number of time slots) is determined based on the fuzzy index. A higher fuzzy index implies that the node is more likely to acquire a time slot.

4.6. Game theory

Game theory [32] models interactions between independent decision-makers, and is particularly suitable for WBANs based on distributed models. Owing to the decentralized and autonomous nature of WBANs, game theory is considered suitable for studying coexistence problems. A game-theoretic model allows a group of players to participate in a game and select cooperative or non-cooperative means to achieve better results with their own strategies. The non-cooperative approach focuses on the utility of an individual user rather than the utility of the entire network. In a non-cooperative game, the objective of all players (i.e., coordinators) is to maximize their gains by modifying their strategy, and ultimately all players will select the strategy with the highest payoff. The situation in which no player can take advantage of one-sided profit by changing his or her strategy is called Nash equilibrium. However, the optimal performance of a network can be achieved through a cooperative approach based on fair means. In a cooperative game, all players consider fairness and Pareto optimality in resource allocation.

4.7. Deep Reinforcement Learning

Deep reinforcement learning (DRL) [33] can be an effective option to jointly optimize resource parameters such as time slots and output power. Schemes based on DRL treat the problem as a model-free Markov decision process (MDP) and transform the optimization problem into maximizing the average reward of the MDP over the processing period. They use a combination of the Q-learning algorithm and a neural network (NN) to determine the optimal policy for handling the state–space explosion and improve network performance. To maximize the long-term utility of the system, the coordinator (i.e., agent) should define a state that can identify the current network condition and a set of actions for optimizing the target parameter values. Then, the

Table 4
Summary of heuristic dynamic resource management mechanisms.

Reference	Objective (improve)	Dynamic parameter	Major consideration	External status information
[34,35]	Energy efficiency, differentiated QoS	Active-sleep cycle	Various traffic patterns	Traffic reception cycle
[36]	Energy efficiency, differentiated QoS	Active-sleep cycle	Different data rate	Abnormal condition of data
[37,38]	Energy efficiency, reliability	Transmission power	Frequent body movement	Gait cycle
[39]	Energy efficiency, reliability	Transmission power, scheduling order	Frequent body movement	On-body link condition
[40]	Energy efficiency, reliability	Transmission power	Frequent body movement	On-body link condition
[41]	Energy efficiency, differentiated QoS	Backoff bounds	Heterogeneous traffic flow	Traffic priority
[42]	Energy efficiency, reliability	Backoff bounds	Heterogeneous traffic flow	Starvation index
[43]	Inter-WBAN interference mitigation	Backoff bounds	Inter-WBAN interference	Severity of interference
[44,45]	Inter-WBAN interference mitigation	Number of time slots	Inter-WBAN interference	Interfering node list
[46]	Energy efficiency, differentiated QoS	Transmission order & slot duration	Frequent body movement	On-body link condition
[47]	Reliability	Number of time slots	Frequent body movement	On-body link condition
[48]	Differentiated QoS	Number of time slots	Heterogeneous traffic flow	Traffic criticality
[49]	Energy efficiency, differentiated QoS	Frame length & sampling start time	Frequent body movement	On-body link condition
[50,51]	Energy efficiency, differentiated QoS	Bit rate	Frequent body movement	On-body link condition
[52]	Inter-WBAN interference mitigation	Beacon period	Inter-WBAN interference	Non-overlapped beacon interval
[53]	Differentiated QoS	Superframe structure	Different sampling rate	Task period of node
[54,55]	Inter-WBAN interference mitigation	Operating channel	Inter-WBAN interference	Degree of interference

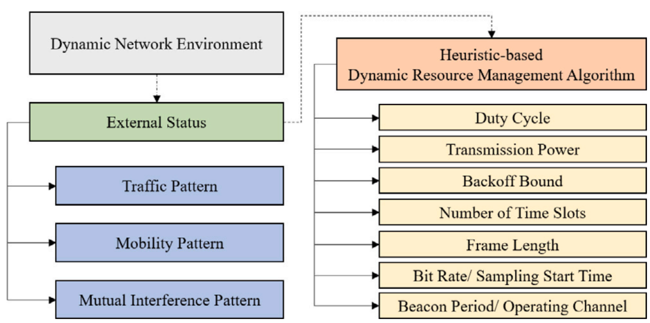


Fig. 5. Heuristic dynamic resource management.

coordinator calculates the reward of the action for each state and learns the policy with the highest Q-value using the NN. In particular, the state definition is of the utmost importance because the current state should concisely summarize previous observations in order that the coordinator predict the subsequent state and future rewards and select the optimal action.

5. State-of-the-art dynamic resource management schemes

Several types of dynamic resource management schemes suitable for WBAN environments have been proposed to increase reliability and resource efficiency, and address the major challenging issues of WBANs. In this section, we review state-of-the-art dynamic resource management schemes according to the classification introduced in the previous section.

5.1. Heuristic dynamic resource management schemes

In WBANs, a probabilistic algorithm capable of responding to a changing environment may be better than a deterministic algorithm, in which the output value to the same input value is always the same. Heuristic resource management schemes are non-deterministic and require external status information. That is, a heuristic algorithm is used to determine a resource allocation policy that can probably lead to the highest performance based on external status information, such as traffic patterns or mobility patterns. Although a heuristic algorithm usually exhibits reasonable performance, it cannot be logically proved that it is always correct. As shown in Fig. 5, a heuristic algorithm obtains external status information and then operates adaptively. Table 4 summarizes heuristic resource management mechanisms.

5.1.1. Dynamic duty-cycle algorithm

Alam et al. [34] proposed a dynamic duty-cycle algorithm to minimize idle energy consumption. To reduce overhearing and idle listening, this algorithm reconfigures the wake-up schedule of the receiving node according to real-time traffic variations of neighboring nodes. To recognize the traffic patterns, the receiver generates a traffic status register (TSR) that contains traffic information of neighboring nodes. When the receiver wakes up according to its own wake-up schedule, it transmits a wake-up beacon frame. If data are received in response to the beacon frame, the TSR corresponding to the sender is filled with the value ‘1’, and if no data are received, the TSR is filled with the value ‘0’. Then, the wake-up intervals are determined according to the content of the TSR for individual nodes. The authors assume that all nodes constituting a WBAN may receive data from neighboring nodes, but a WBAN is based on a one-hop star topology in which the data collected by sensor nodes are transmitted to the coordinator through single-hop transmission. That is, it appears more reasonable that the coordinator should adaptively determine the duty cycle according to the data rate and QoS requirements of individual nodes than that all nodes should adjust their wake-up intervals based on the traffic patterns of neighboring nodes.

Zhang et al. [36] proposed a dynamic duty-cycle MAC protocol for low-data-rate WBANs. High-data-rate WBANs have the advantage of being able to continuously monitor the health condition of a patient, but they consume excessively large amounts of energy. By contrast, low-data-rate WBANs transmit physical information to the coordinator when abnormal conditions are detected. To maximize energy efficiency, this MAC protocol maintains the duty cycle of nodes at a very low level, whereas differentiated QoS for abnormal data is supported by adaptively adding short insertion time slots to the superframe after recognizing the traffic fluctuation. In addition, the coordinator uses a longer superframe structure to reduce the energy consumption caused by the reception of duplicate beacon frames. However, the authors do not discuss the detection of emergent events in detail, nor do they consider the frame drop caused by body shadowing.

Olatinwo et al. [35] proposed an energy-aware hybrid MAC protocol. To provide a differentiated QoS for critical node and increase energy efficiency, the authors combine both the CSMA/CA and time-division multiple access (TDMA) schemes. The proposed scheme classifies the user data into critical and normal data based on the WBAN application requirements. In the CSMA/CA phase, only the nodes that have packets to send will contend for transmission opportunities. In the TDMA phase, an adaptive timeslot scheduling is applied to adjust the duty cycle of the nodes with normal data packets. To reduce idle listening, the authors introduced a sleep–wake-up scheduling scheme. Each node has a passive wake-up radio, which is a special type of radio to turn off the main radio when it is not transmitting data to minimize unnecessary power consumption. When the coordinator transmits the request to receive (RTR) beacon, the wake-up radio generates an interrupt signal to turn on the main radio, and only the nodes that have packets to send contend for transmission slots.

5.1.2. Dynamic TPC mechanism

Quwaider et al. [37] proposed a dynamic body-posture-based TPC scheme to ensure a balance between energy consumption and packet loss. Specifically, the authors developed a dynamic postural position inference mechanism in which on-body link characteristics are used to infer the current postural position. This system determines the current body posture based on received signal strength indicator (RSSI) measurements at the receiver. In addition, through quantitative experiments based on an actual WBAN system, they determined the RSSI threshold range (−88–−82 dBm) to balance packet loss and energy consumption. The proposed algorithm determines the current body posture by defining the relationship between the power level index (i.e., X-axis) and RSSI (i.e., Y-axis) as a linear equation. When the linear equation for a new position is obtained, the transmission power level can be calculated by specifying the desired RSSI as the middle value of the predefined threshold range. However, the transmission power level may be outdated owing to the highly dynamic nature of WBANs, severely degrading the performance of TPC mechanisms.

Zang et al. [38] proposed an accelerometer-assisted dynamic TPC algorithm for energy-efficient communications. The authors claim that energy efficiency can be improved by optimizing the power required for successful transmission between the sensor node and the coordinator. The conventional dynamic TPC algorithm determines the transmission power based on the link quality of the received data packet, but it is possible that the current link information is already outdated owing to the highly dynamic on-body link characteristics of WBANs. To address this, the proposed TPC algorithm exploits periodic link-quality fluctuations. To define the relationship between body movement and channel periodicity, the proposed TPC algorithm recognizes the current body movement using an accelerometer, implying that the acceleration signal and the RSSI of the packet have the same period. Then, the sensor node transmits the packet with the minimum transmission power at the time point with the best link quality, or increases the transmission power level using feedback information to prevent long time delays. However, this scheme does not provide a suitable TPC solution for aperiodic behavior.

Zhang et al. [39] proposed a dynamic TPC and slot-scheduling scheme to achieve a better trade-off between reliability and energy consumption. Initially, all nodes are assigned their own scheduled upload interval (SUI) with the same length in the superframe to satisfy the "fairness constraint". To avoid deep fading owing to body movements, the authors proposed a temporal autocorrelation model in which the coordinator tracks the link quality of all sensor nodes based on RSSI measurements, and predicts the channel condition in the next TDMA round. Using the predicted channel condition, the coordinator adjusts the SUI order and transmission power. For example, the coordinator rearranges the SUI according to node link quality to increase the probability of successful transmission. The transmission power is determined to be higher than Rx sensitivity (i.e., RSSI threshold) considering the channel variation in the next round. However, if the resource allocation policy for the next TDMA round is determined based on the historical RSSI information without considering on-body channel characteristics, satisfactory performance is expected only in a static scenario with little user activity.

Zhang et al. [40] proposed a relay-aided dynamic TPC method to ensure transmission reliability and save energy. The authors argue that the transmission power level should be adaptively changed to handle changes in link quality according to body movements. The average channel condition is calculated using the RSSI records of the packets received in the previous beacon period. The coordinator calculates the transmission power level required for successful transmission based on the average channel condition, and broadcasts the corresponding information to the nodes through a beacon frame. In addition to the dynamic TPC mechanism, an adaptive transmission method using a relaying node was proposed. It is designed to handle the long-distance problem and ensure transmission reliability. For example, if the channel condition between the coordinator and the source node is expected to be "bad" (i.e., lower than the RSSI threshold), the coordinator notifies the source node to perform relay-aided two-hop transmission. As explained above, RSSI-based predictive models exhibit significant performance fluctuations in a dynamically changing WBAN environment; however, the authors did not consider a human mobility model in the process of performance evaluation.

5.1.3. Dynamic backoff algorithm

Saboor et al. [41] proposed a dynamic backoff scheme that uses a non-overlapping contention window (CW) to increase energy efficiency by reducing collisions between nodes with different traffic priorities. The authors point out that doubling the CW size when an even number of collisions occur in the existing binary exponential backoff algorithm is the main reason for reducing superframe utilization (it should be noted that the backoff number (β) for each node is randomly initialized to a random value between 1 and CW), whereas an additional sliding window (SW) is introduced, and the SW value is increased by 2 when an even number of collisions occur. Initially, β is initialized to a random value between CW_{min} and CW_{max} defined in advance according to the traffic priority (i.e., 0–7, as shown in Table 2). If the channel is idle, β decreases by 1, and data are transmitted when β becomes zero. If an even number of collisions occur, CW_{min} is recalculated by the minimum value between SW and window limit. Shortening the CW range can reduce the idle listening time so that the superframe can be used more efficiently. In addition, the probability of collisions and retransmissions can be reduced because a non-overlapping CW is adopted according to traffic priority. However, the short CW range is effective only in the case of low node density, and as the traffic priority is not determined at runtime, there is a limitation in providing differentiated QoS according to changes in traffic patterns and traffic context. Studies with a similar concept can be found in [56].

Fourati et al. [42] proposed a dynamic backoff bound assignment algorithm based on network traffic status to provide better service differentiation. The authors argue that nodes with low priority suffer from long waiting times and starvation in heterogeneous WBANs. To resolve this, the proposed algorithm uses a new parameter (starvation index) and constantly changes the CW bounds during the transmission process. Initially, the starvation index is set to 0 and increases by 1 whenever the channel is busy or retransmission occurs. When an even number of collisions occur, the CW bounds are adjusted according to the starvation index. By counting the number of retransmission attempts and estimating the waiting time of a given packet, the proposed mechanism ensures a balance between low-priority and urgent traffic. However, the main cause of retransmission is channel fading rather than collision, and thus the performance of the proposed mechanism is highly dependent on body movements.

Velusamy et al. [43] proposed a dynamic backoff mechanism to mitigate inter-WBAN interference. The authors argue that to reduce the packet loss caused by mutual interference between adjacent WBANs, the channel contention method using CSMA/CA is more suitable than the slot scheduling method. To mitigate the mutual interference, the proposed backoff algorithm dynamically adjusts CW size according to the severity of the interference. For example, if a collision occurs between sensor nodes owing to interference between adjacent WBANs, these nodes exponentially increase the CW size to decrease the probability of channel acquisition. The initial CW size is also dynamically calculated according to the buffer status, that is, a node with a large amount of data in the buffer has a higher probability of obtaining a channel. The proposed algorithm has the advantage of lowering the collision probability without explicit channel usage agreement between adjacent coordinators. However, this scheme cannot support QoS for emergency traffic. In addition, as the number of adjacent WBANs increases, the slot scheduling method can be more efficient than the CSMA/CA-based CW adjustment mechanism.

5.1.4. Dynamic scheduling algorithm

Khan et al. [44] proposed a dynamic scheduling algorithm to mitigate inter-WBAN interference. The authors developed an interference detection algorithm that indicates the degree of interference between WBANs. In this algorithm, each coordinator adds a sensor node located in the interference region to the interfered sensor list. Then, the coordinators exchange their interfered node lists and generate a common interference region. Based on the common interference information, each coordinator schedules at least one non-interfered node with the highest priority, and only one interfered node with the highest priority in the first time slot. It should be noted that interfering nodes are scheduled first at every time slot. The authors claim that this mechanism is advantageous, as spatial reuse is improved for future time slots. However, the disadvantage of the algorithm is that superframe length increases according to the number of coexisting WBANs.

Liu et al. [46] proposed a dynamic slot allocation scheme to increase energy efficiency and maintain QoS. The proposed scheme dynamically adjusts the transmission order and duration based on the channel condition. A two-state Markov process is proposed to recognize the on-body channel condition between all sensor nodes and a coordinator during a specific mobility pattern. One state (i.e., good state) indicates successful transmission of a packet, and the other state represents packet loss (i.e., bad state). The transmission ordering rule assigns a time slot to the "good" nodes at the beginning of the superframe before all "bad" nodes. This ordering rule allows reliable transmission, but it is also important to determine the transmission duration (i.e., number of slots) of nodes so that QoS requirements may be met. To this end, the proposed scheme recognizes the context variation of the person through a context-awareness algorithm and adaptively adjusts the sampling rate and the number of slots. However, the proposed technique has a limitation in that it cannot recognize detailed channel conditions because the on-body channel state is determined only through the two-state Markov model.

To reduce the packet loss ratio caused by body shadowing, Zhang et al. [47] proposed a dynamic slot scheduling scheme based on channel autocorrelation. The authors claim that the existing dynamic scheduling scheme based on the Markov model is insufficient for recognizing the on-body channel state because it classifies the channel state into only two states: "good" or "bad". To resolve this, the proposed mechanism uses the temporal autocorrelation of on-body links in daily activity scenarios. Analysis of actual on-body channel gain data using a custom wireless transceiver demonstrated that the temporal autocorrelation of on-body channels within a time lag of 500 ms is important. Hence, the proposed temporal autocorrelation model captures the channel-gain variation within a time lag of 500 ms. The coordinator uses the temporal autocorrelation model to predict the on-body channel condition for future time slots and then optimizes the permutation of the time slots for the connected sensor nodes. However, the proposed mechanism adds an additional subslot at the beginning of every beacon period to track the channel-gain variation, thus increasing the control overhead. Moreover, the time threshold (i.e., 500 ms) for decision making depends on empirical data.

To minimize the transmission delay of urgent packets, Ambigavathi et al. [48] proposed a dynamic slot scheduling algorithm based on traffic priority. By default, the coordinator allocates dedicated time slots to the nodes in order of priority for medical applications. For more flexible decision making at runtime, the proposed scheme classifies the data traffic according to criticality: low- and high-threshold traffic. That is, for sensor nodes with the same priority, the coordinator can reduce the risk of conflict in slot allocation by using another condition (i.e., the criticality of the recently received data) in the scheduling process. This decision-making method based on combinations of various conditions assists coordinator in performing adaptive slot allocation. However, there is a limitation in handling unexpected network conditions such as frequent body movements.

Fan et al. [45] proposed an exchange-free resource scheduling scheme for interference alleviation in dynamic coexisting WBANs. In the proposed scheme, the superframe is divided into two phases: data transmission phase and data retransmission phase. The data transmission phase, a timeslot scheduling scheme is designed based on a Latin square to reduce channel conflicts. The Latin square indicates specific combinations of available timeslots and channels, which ensures that there is no intra-WBAN interference and the probability of inter-WBAN interference is low. In the data retransmission phase, a retransmission timeslot selection scheme is devised based on a hash function, in which the unique identity information of the collided node is used to determine the retransmission slot.

5.1.5. Dynamic frame length optimization

Sun et al. [49] proposed a dynamic data frame length optimization method to improve the QoS and energy efficiency. The authors point out that even if only a small portion of the data in a frame fails, all the data are retransmitted. To address this, the proposed scheme defines a relationship between the delivery probability and data-frame length according to the on-body channel condition. In the proposed method, each sensor recognizes the channel state according to the signal-to-interference and noise ratio (SINR), and if the channel-condition variation is large, the original data frame is divided into several data frames, thereby increasing the delivery probability. However, as a data frame has fixed header bits, such as MAC frame header and frame checking sequence, reducing the data-frame length can increase the overall control overhead.

5.1.6. Dynamic bit rate & sampling start time adaptation

Cwalina et al. [50] proposed a dynamic bitrate adaptation method to increase resource efficiency. The authors argue that resource efficiency can be improved by reducing the number of bits lost owing to fast fading. The proposed method determines the LOS/NLOS conditions by using RSSI and global information about the distance between sensor nodes. To minimize signal power fluctuations owing to channel fading, the on-body channel condition is predicted using the NOS/NLOS conditions. Then, the bitrate is maximized when noise is discontinuous (i.e., if the signal is strong, high data-rates are adopted, whereas low data-rates are adopted during weak signals). Essentially, the sensor data-rate is highly dependent on the sampling rate required for a certain application, and thus the proposed scheme cannot ensure minimum throughput when deep fading constantly occurs.

Liu et al. [51] proposed a dynamic transmission rate adaptation method to minimize energy consumption considering QoS constraints. The authors argue that a low packet loss rate (PLR) can be obtained by lowering the transmission rate, but energy consumption increases because of the longer transmission time. Accordingly, the proposed method calculates the constraints related to QoS metrics, such as PLR, throughput, and delay for data packets, using mathematical formulas. If the current transmission rate satisfies the PLR constraint with the maximum transmission power, the transmission rate is maximized to reduce energy consumption. Conversely, if the transmission rate threshold that satisfies the PLR constraint with the maximum transmission power is less than the minimum transmission rate, the transmission rate is minimized. However, reducing the transmission rate to reduce the PLR increases the number of dedicated time slots in a superframe so that the throughput constraint can be satisfied. In addition, as the QoS constraints are calculated based on the maximum output power, the proposed scheme cannot optimize transmission power.

Sun et al. [49] proposed a dynamic sampling start time adaptation method to reduce the average data frame delay, along with the previously described data frame length optimization scheme. In the proposed method, each node must wake up for sampling at a time point close to the scheduled transmission time so that the node can directly encapsulate the data generated by sampling and insert the data frame into the buffer queue. Thereby, the proposed method can reduce the sleep delay between the sampling start time and transmission start time, and prevent buffer overflow owing to the accumulation of old data frames. However, the transmission delay significantly increases if channel fading occurs during the scheduled transmission time. That is, the performance of the proposed scheme is highly dependent on the slot scheduling scheme, but the authors did not address this issue.

5.1.7. Dynamic beacon period & channel selection algorithm

Iqbal et al. [52] proposed a dynamic beacon shifting scheme to reduce packet loss caused by inter-WBAN interference. In the proposed scheme, a BAN recognizes coexisting BANs by receiving beacon frames from adjacent BANs. One of these BANs becomes a cluster head and broadcasts a command frame, and a non-overlapping beacon period is calculated using the information (i.e., duration of beacon phase) included in the acknowledgment (ACK) frame received from all interfering BANs. This method, in which the beacon period is calculated by a centralized coordinator, is very simple and has low complexity, but the major drawback is the increase in the control message overhead as well as the lengthening of the beacon interval as the number of coexisting BANs increases.

Chen et al. [53] proposed a dynamic superframe interleaving scheme with beacon shifting to improve bandwidth utilization and communication QoS in intra-WBANs. The authors argue that as WBAN nodes have different task periods and delay constraints, depending on the sampling rate and data rate, each node can share the same frequency band by changing the task periods through active superframe interleaving. In the proposed method, the task periods of nodes are dynamically adjusted according to their delay constraints. Each beacon period consists of four quarters in which the transfer operation can exclusively occupy at least one quarter. It also adopts n-periodic allocation based on the longest delay constraint to save more beacon periods. However, the proposed scheme does not exhibit satisfactory performance in a coexisting-WBAN environment because the active superframe interleaving technique is used to mitigate the mutual interference between neighboring WBANs rather than to improve intra-WBAN bandwidth utilization.

Tseng et al. [54] proposed a dynamic channel-hopping algorithm to reduce the transmission delay caused by inter-WBAN interference. The average degree of channel interference is recorded as a weighted moving average to prevent erroneous prediction of the channel condition owing to short-term historical data. The proposed method generates a channel-state table to record the historical status of each channel, and then calculates the X value representing the degree of channel interference. This value is used to select a suitable channel for the next transmission. That is, the channel with the smallest X value is selected as the next hopping channel because a smaller value of X implies a lower degree of interference. In addition, another rule of the proposed scheme is that channel separation is considered to prevent interference of adjacent channels. For example, if a node selects channel C_6, other nodes do not select adjacent channels (i.e., C_5 and C_7) as a hopping channel. However, this rule is only valid if there are sufficient operating channels. In addition, if the number of coexisting WBANs is greater than the number of available channels, an additional coexistence mechanism is required to share limited bandwidth resources.

Ashraf et al. [55] proposed an energy-efficient dynamic channel allocation algorithm. The proposed scheme aims to exploit the benefit of polling access mechanism of the IEEE 802.15.6 standard by dynamically assigning timeslots for heterogeneous sensor nodes. Specifically, the proposed scheme dynamically allocates timeslots for devices with high data rate using a single demand control packet. The coordinator allocates required polling slots when receiving a demand control packet. If there are no free timeslots, the requesting node should wait for next superframe. These dynamic assignments of polling slots for nodes with higher traffic demand can reduce additional energy consumption and provide differentiated service to nodes with critical signals in emergency situations.

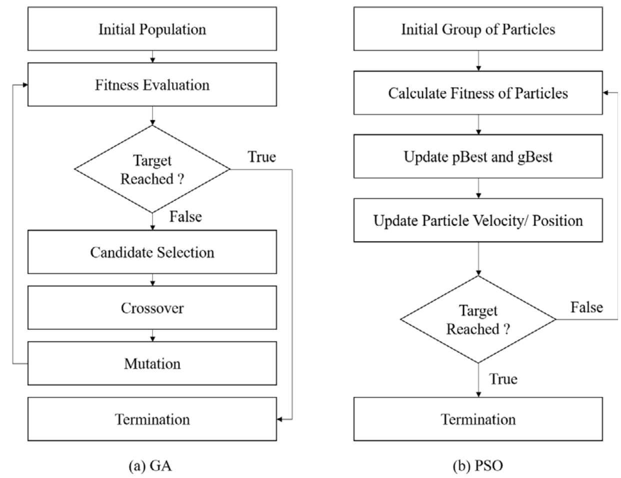


Fig. 6. Basic structure of evolutionary algorithms: (a) GA, (b) PSO.

5.2. Dynamic resource management schemes based on evolutionary algorithms

In WBANs, two types of evolutionary algorithms are used to address optimization issues: genetic algorithms (GAs) and particle swarm optimization (PSO). As previously explained, they are used for transmission power optimization. Ant colony optimization (ACO) is also used, but it is not considered here because it is primarily applied to routing path optimization.

GAs are global optimization techniques based on the evolutionary process of the natural world. A GA represents candidate solutions as a data structure (i.e., gene) and then transforms them (i.e., evolution) to obtain better solutions. As shown in Fig. 6(a), a GA obtains the optimal solution through three genetic operations: selection, crossover, and mutation. The selection process generates an advanced group by probabilistically selecting candidate solutions that optimize the fitness function from the random initial group. The crossover process intersects the binary code between candidate solutions from the advanced group. The mutation process randomly changes some codes of each candidate solution to form an offspring group. Finally, the offspring group is applied to the fitness function to search for an optimal solution, and the current generation ends when these processes are completed.

Particle swarm optimization is a simple global optimization technique inspired by the group behavioral characteristics of animals such as birds and fish. It exchanges information between several candidate solutions and simultaneously improves them through iterative calculations, thereby finally achieving the optimization of the objective function (i.e., fitness function). The solution to the problem is expressed as a particle, and individual particles have the properties of “position” and “velocity”, As shown in Fig. 6(b), each particle moves to the next position by referring to the local optimal solution (i.e., pBest) and global optimal solution (i.e., gBest). The current generation terminates when all particles move one step forward. For each generation, the fitness for the next position is calculated using the objective function, and pBest and gBest are updated. Finally, when the number of generations reaches a predefined value, the optimization process is completed.

5.2.1. Dynamic TPC mechanism based on Genetic Algorithms

Kazemi et al. [57] proposed a dynamic transmission power optimization GA scheme to maximize throughput and energy efficiency by mitigating the mutual interference between adjacent WBANs. The proposed scheme uses a fuzzy power controller (FPC) system to determine the optimal transmission power according to the state of the input value (e.g., “low”, ”medium”, and “high”). The current interference power level and SINR are used as input values to the FPC system, and the

Table 5
Summary of graph coloring dynamic resource management mechanisms.

Reference	Objective (improve)	Coloring rule	Dynamic parameter	Extra coloring information	Incomplete coloring
[61]	Inter-WBAN interference mitigation	Oriented vertex coloring	Number of time slots	–	Yes
[62]	Inter-WBAN interference mitigation	Oriented vertex coloring	Number of time slots	Interference pattern	No
[63]	Inter-WBAN interference mitigation	Oriented vertex coloring	Number of time slots	Weighted color set	Yes
[64,65]	Inter-WBAN interference mitigation	Oriented vertex coloring	Operating channel	Color sequence list	Yes
[66]	Inter-WBAN interference mitigation	Oriented vertex coloring	Operating channel	Two-hop coloring information	Yes

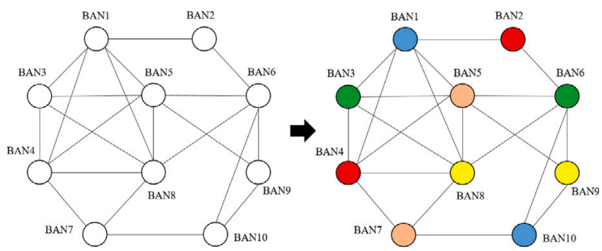


Fig. 7. An example of graph coloring problem.

output (i.e., transmission power level) in the previous step is reused as an input for feedback. The feedback input is used to optimize the fitness function in the FPC system. By using three genetic operations, the GA determines the optimal transmission power level that maximizes a given fitness function.

5.2.2. Dynamic TPC mechanism based on Particle Swarm Optimization

Kaushik et al. [58] proposed a dynamic transmission power optimization scheme using PSO. The authors emphasize that it is important to determine the optimal transmission power according to the distance between the coordinator and the sensor node to save energy and prevent damage to body tissues. The proposed scheme maintains the minimum transmission power to prevent tissue damage and calculates the distance (i.e., threshold distance) at which the received power is maximized according to the on-body channel condition. Transmission power can be further optimized by using the threshold distance as a constraint parameter of the objective function in PSO. However, as the proposed scheme does not regard global information as an important factor necessary to optimize the transmission power of individual nodes, PSO cannot be applied to the proposed scheme. In fact, PSO is primarily used for path optimization for temperature-aware routing [59,60] in WBANs.

5.3. Graph coloring dynamic resource management schemes

As shown in Fig. 7, the graph coloring problem is concerned with coloring a non-directional graph with different colors so that adjacent vertices do not have the same color. Inter-WBAN interference can be modeled as a graph coloring problem. That is, different channels or time slots should be allocated to coexisting WBANs so that WBANs with overlapping communication ranges do not share a certain resource at the same time.

There are two types of graph coloring rules: non-oriented and oriented vertex coloring. In the former, when a color conflict occurs between two vertex pairs, a new color is considered in the next coloring round. Conversely, in oriented vertex coloring, the color is assigned to the vertex with the higher priority. That is, oriented vertex coloring results in at least one winner for each coloring round. Table 5 summarizes graph coloring resource management mechanisms.

5.3.1. Dynamic scheduling algorithm

Cheng et al. [61] proposed a dynamic inter-WBAN scheduling scheme for high spatial reuse and low time complexity. The proposed scheme is based on oriented vertex coloring that uses predefined edge orientation (i.e., vertex priority) for high coloring speed. However, the authors argued that predefined vertex priority is not suitable for the dynamic topology of WBANs. To ensure fairness, the authors proposed a random value coloring method that adopts a random value comparison to produce an instant priority difference between all adjacent vertices. Moreover, to achieve spatial reusability, they proposed an incomplete coloring method that modifies the conventional coloring rule. This coloring method can avoid color conflicts by allowing uncolored vertices in case of color scarcity, implying that uncolored vertices (i.e., WBANs) become temporarily inactive and do not interfere with neighboring WBANs.

Huang et al. [62] proposed a distributed coloring algorithm to construct an interference-free time-slot schedule. The principle of the proposed scheme is that each WBAN attempts to randomly color all uncolored nodes (i.e., interfering nodes), and the higher-priority node wins the color in each round. To maximize coloring in each round, the proposed algorithm adopts a two-phase approach. In the first phase, each WBAN learns the received power from the coexisting WBANs by negotiating global time slots to transmit data in turn. Thereby, WBANs learn the interference patterns of other WBANs and construct an interference graph. In the next phase, each WBAN assigns a color to the local interfering node using the interference graph, and exchanges the coloring information with adjacent WBANs so that higher-priority nodes win the overlapped color (i.e., time slot). As a result, each WBAN can color multiple nodes in a single round with minimal color conflict.

Seo et al. [63] proposed a dynamic scheduling method to avoid interference with adjacent WBANs. The proposed technique uses a weighted color set to modify the incomplete coloring method. The weighted color set is used to allow a vertex with a lower probability of color conflict to more choose a color (i.e., time slot). The proposed scheme has a counting value that increases by one for each coloring round if the selection of a color does not lead to conflicts, and is used to create a weighted color set. Each WBAN selects a color (i.e., the coordinator assigns a time slot to the interfering node) with the highest weight from the weighted color set, and then exchanges the coloring information with neighboring WBANs. If a color conflict occurs, each WBAN wins a color based on a random value. WBANs that have lost the competition are not colored to enhance the coloring speed.

5.3.2. Dynamic channel selection algorithm

Lee et al. [64] proposed a distributed multi-coloring scheme for coexistence mitigation. Each WBAN first broadcasts its own information (i.e., color and priority) to gather two-hop neighbor information. Then, each WBAN randomly selects a color (i.e., channel) and compares the color and priority with those of its neighbors. If the WBAN selects the same color as that of the neighboring WBANs, the highest-priority WBAN acquires the color. If the WBANs have the same priority, they select a random integer value from 1 to 100. Thus, the WBAN with the highest integer value obtains the color. After the initial coloring phase, the proposed multi-coloring scheme produces a color sequence that represents the list of available colors generated in the initial coloring phase. The color sequence is generated using the maximum overlapped degree, which is the number of overlapped neighbors within two-hop distance. If a color conflict occurs, the WBAN checks its color sequence and reselects the initial color. As a result, each WBAN has multiple colors, and the proposed algorithm can improve spatial utilization.

Wu et al. [66] proposed a distributed incomplete coloring scheme to maximize channel reuse. Given a graph G (i.e., WBANs) and number

Table 6
Summary of MCDM-based dynamic resource management mechanisms.

Reference	Objective (improve)	MCDM model	Dynamic parameter	Evaluation criteria
[67]	Differentiated QoS	AHP	Number of time slots	Critical index, buffer size, frequency level
[68,69]	Differentiated QoS, energy efficiency, prevention of tissue damage	AHP	Number of time slots	PER, estimated temperature, average power consumption
[70]	Differentiated QoS	AHP	Number of time slots	Traffic user priority, WBAN priority, severity index
[71]	Inter-WBAN interference mitigation	AHP	Operating channel	Frame reception ratio, traffic type ratio, average power consumption

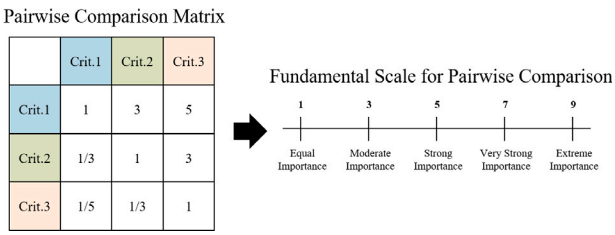


Fig. 8. An example of pairwise comparison (AHP).

of colors k (i.e., channels), the proposed scheme yields an incomplete coloring solution with the maximum number of colored vertices. As described previously, the incomplete coloring method [61] allows some vertices to be left uncolored, resulting in more flexible coloring. Based on this observation, the authors proposed a distributed incomplete coloring algorithm that uses two-hop coloring information to determine the local color in each WBAN. The proposed approach imperfectly colors vertices within two-hop distance, allowing other vertices outside the two-hop radius to use more colors. Therefore, vertices can more easily find available channels when a color conflict occurs owing to a change in the graph topology.

Ma et al. [65] proposed an unsupervised coloring algorithm to mitigate channel interferences. The authors argue that existing coloring algorithms require frequent monitoring of the channels used by the surrounding WBANs, which incurs significant power consumption. Moreover, inaccurate location information degrades the performance of spectrum allocation. Specifically, the authors use k-means++ algorithm to implement the self-organizing partition of WBAN. Based on the Euclidean distance, the proposed scheme partitions the WBAN nodes and allocates channel groups to each cell by vertex coloring. Through the channel group assignment, the proposed scheme can reduce the frequency of traversal and power consumption compared with the conventional graph coloring algorithms.

5.4. Dynamic resource management schemes based on multi-criteria decision-making

To efficiently use a given resource, it is necessary to allocate it considering cognitive metrics, such as mobility, energy, and link quality. However, the use of correlated or unrelated metrics inevitably leads to complex decision-making problems. In WBANs, MCDM assists in making the best decision for resource allocation (e.g., operating channel selection and time slot allocation). It is a series of processes that make a preferred decision regarding the available alternatives. Among MCDM methods, analytic hierarchy process (AHP) [72] is primarily used for adaptive decision-making considering the current network condition.

It relies on a hierarchical computational model based on human reasoning. It reduces the complexity of the decision process to a series of pairwise comparisons and then aggregates the results. That is, it requires pairwise comparisons to determine the relative importance of the evaluation criteria. As shown in Fig. 8, the pairwise comparison is represented by a square matrix X_{ij}, where X_{ij} is the preferred scale of factor i to j. Then, it generates a normalized eigenvector (i.e., weighted value) for each criterion based on the result of the pairwise comparison. The initial pairwise comparison matrix (X_{ij}) is defined by a decision maker (i.e., protocol designer) considering the network environment. Table 6 summarizes MCDM-based resource management mechanisms.

5.4.1. Dynamic scheduling algorithm

Roy et al. [67] proposed a dynamic scheduling algorithm to support differentiated QoS. The proposed method calculates the priority values of the sensors, and subsequently it ranks the sensors according to priority for time-slot allocation. In the priority calculation, three evaluation criteria, namely, critical index, buffer size, and frequency level, are considered, and the weighted values of each criterion are derived through AHP, where the weighted values are calculated using the pairwise comparison matrix (i.e., scales of preference) determined by a decision maker according to the network condition. Then, the coordinator normalizes the actual values of the evaluation criteria and multiplies them by the weighted values of each criterion to derive a weighted sum. The coordinator prioritizes the sensor nodes based on the weighted sum, and then allocates time slots according to priority.

Kim et al. [68] proposed a priority-based dynamic scheduling algorithm to prevent damage to body tissues and resource waste. The scheduling order is determined according to node priority, derived through AHP. To calculate node priority, the proposed algorithm considers three evaluation criteria: PER, estimated temperature, and average power consumption. The preferred scale of the pairwise comparison matrix is dynamically adjusted according to several test scenarios, such as a situation in which the nodes frequently move, and body temperature reaches a certain threshold. That is, the scheduling order changes dynamically depending on the proposed three parameter values and the scale of the pairwise comparison matrix. In addition, if the number of time slots requested by the nodes is greater than the scheduled uplink interval, optimization is performed. In the optimization phase, the slot with the lowest scheduling order is removed from the scheduled uplink interval until the length limit is satisfied.

Yuan et al. [70] proposed a dynamic channel access ordering scheme to guarantee the transmission privilege of critical data in a coexisting WBAN environment. The proposed scheme introduces a critical health index to determine the transmission order of the nodes. The critical health index considers three evaluation criteria: traffic user priority, WBAN priority, and severity index, and is calculated through AHP. The authors set the preferred scale of the pairwise comparison matrix as follows: WBAN priority is more important than traffic priority. Data severity is much more important than traffic priority and WBAN priority. For example, the node that generates the abnormal data has a higher health critical index than the normal node, and thus gains a higher priority for channel access. Each WBAN shares the same operating channel and exchanges the interfering node sets. Then, each WBAN determines the service order of the nodes after sorting them in descending order based on the health critical index.

Kim et al. [69] proposed a dynamic scheduling algorithm to achieve multi-objective optimization. The authors aim to jointly satisfy the temperature constraints and QoS requirements by dynamically managing the available resources at the MAC layer. Since the total length of the superframe is limited to 255 ms, the coordinator should adaptively distribute the available radio resources to provide a differentiated QoS and suppress the temperature increase. The make the best decision, the

Table 7
Summary of fuzzy-theoretic dynamic resource management mechanisms.

Reference	Objective (improve)	Dynamic parameter	Fuzzy input	Fuzzy output variable
[73]	Energy efficiency, differentiated QoS	Number of time slots	Packet delivery rate, energy ratio, buffer ratio	Fuzzy GTS priority
[74]	Differentiated QoS	Number of time slots	Collision rate, data rate	Fuzzy GTS priority
[75]	Differentiated QoS	Backoff bounds	Channel clear rate, sample rate	Fuzzy maximum delay
[76]	Differentiated QoS	Backoff exponent	Number of backoff rate, data rate	Fuzzy backoff exponent
[57]	Energy efficiency, differentiated QoS	Transmission power	Interference power level, current transmission power level, SINR	Transmission power level

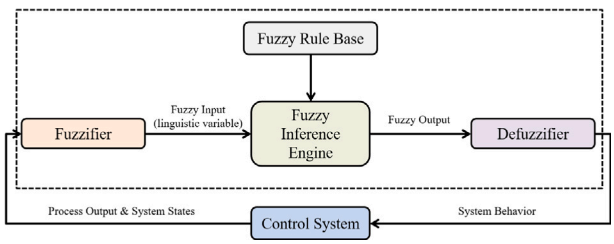


Fig. 9. Basic structure of FLS model.

proposed scheme considers multiple cognitive metrics, namely, priority level, temperature level, and link quality in the scheduling process. To incorporate the cognitive metrics into the decision-making, the authors adopt the MCMD method. Specifically, the proposed scheme determines the relative importance of the decision metrics using AHP and calculates a critical index, which indicates the criticality of each node under the current network condition. Based on the critical index, the coordinator can determine the scheduling order for each node.

5.4.2. Dynamic channel selection algorithm

Kim et al. [71] proposed a dynamic channel selection algorithm for coexistence mitigation. The proposed algorithm maximizes the use of multiple channels by adaptively selecting the best channel, considering various decision-making factors through AHP. Three evaluation criteria, namely, frame reception ratio, traffic type ratio, and average power consumption, are used to determine the optimal channel. The preferred scale of the pairwise comparison matrix is determined according to WBAN type. For example, in a medical WBAN, frame reception ratio is more important than the others. By contrast, in a consumer electronics WBAN, traffic type ratio is the most important factor. Finally, each WBAN selects a channel with the highest weighted sum of these criteria.

5.5. Fuzzy-theoretic dynamic resource management schemes

In WBANs, fuzzy theory is used to handler ambiguous network parameters. For example, when a time slot is allocated to a node, it would be advantageous to allocate the radio resource to a node with low mobility, sufficient residual energy, and high link quality. However, ambiguous expressions such as "low" and "high" cannot be represented in conventional logical structures because the corresponding range of values is not clear. In an FLS, the linguistic inputs are normalized, and the output (i.e., fuzzy index) is derived from the range 0–1. Then, system behavior is defined based on the fuzzy index.

As shown in Fig. 9, an FLS has four basic components: a fuzzifier, a fuzzy rule base, a fuzzy inference engine, and a defuzzifier. It determines the optimal solution through three control processes: fuzzification, fuzzy inference, and defuzzification. Fuzzification is the process of converting crisp inputs into linguistic values and membership function according to a fuzzy inference rule. In the fuzzy inference process, inference is performed using the membership value derived through fuzzification. Defuzzification converts the fuzzy output into a numerical value to define the system behavior. Table 7 summarizes fuzzy-theoretic resource management mechanisms.

5.5.1. Dynamic scheduling algorithm

Pushpan et al. [73] proposed a dynamic scheduling algorithm to reduce wasted time slots and excessive delays. The proposed scheme uses fuzzy logic with the following input variables: packet delivery ratio (PDR), energy ratio, and buffer ratio. The fuzzy model uses three linguistic terms (low, medium, and high) to differentiate the input variables. The term for each input value is defined through a membership function, and a fuzzy inference rule is determined through a series of conditional statements of "if-then". For example, if a linguistic value is high (e.g., PDR is high), then the allocated slot value is determined as high, and other conditions follow the same rule. That is, if the normalized input values for PDR, energy ratio, and buffer ratio are all high, then the probability of acquiring the required time slots will increase as the fuzzy index is maximized.

Nekooei et al. [74] proposed a dynamic scheduling algorithm to enhance communication reliability. The proposed scheme dynamically prioritizes GTS allocation according to different QoS requirements and channel conditions. In the proposed FLS, the collision rate and data rate are used as fuzzy inputs, and $fuzzyGTSpriority$ is derived as the output. $fuzzyGTSpriority$ is divided into four separate fuzzy levels: $P1$, $P2$, $P3$, and $P4$. Fuzzy inputs are converted to the linguistic values low, medium, and high, and the priority for GTS allocation is determined by fuzzy inference rules. For example, for a node with a high collision rate or low data rate, FLS recommends the lowest priority $P1$ to prevent wasting GTS resources. Finally, the coordinator performs GTS allocation by sorting the nodes according to the $fuzzyGTSpriority$ level.

5.5.2. Dynamic backoff algorithm

Mouzehkesh et al. [75] proposed a dynamic backoff algorithm to improve the overall latency and reliability. To maintain a good balance between waiting time and channel condition, the proposed FLS uses the channel clear rate and sample rate as fuzzy inputs. $FuzzyMaxDelay$ is derived as the fuzzy output, and the backoff delay is determined using the $FuzzyMaxDelay$ level (i.e., $D1$ to $D6$). According to the fuzzy inference rule, if a node has a high channel clear rate during the last n superframes, and has a medium sample rate, the node is assigned a moderate value of $FuzzyMaxDelay$. Thus, the node is more likely to access the channel, and other nodes have a lower channel access probability.

Nekooei et al. [76] proposed a dynamic backoff exponent (BE) scheme to improve network reliability. The proposed scheme represents the level of channel busyness as the value of backoff rate (NB_{rate}), and determines the BE using a combination of the busy history of the channel and the data rate of the application. That is, NB_{Rate} and data rate are used as fuzzy input, and $fuzzyBE$ is derived as fuzzy output. The $fuzzyBE$ is divided into four levels, and the node with the lowest $fuzzyBE$ level has a relatively high chance to acquire the channels. For example, the proposed FLS suggests the lowest level of $fuzzyBE$ when both NB_{rate} and data rate are low to increase channel utilization.

5.5.3. Dynamic TPC mechanism

Kazemi et al. [57] proposed a dynamic TPC mechanism to maximize throughput and energy efficiency by mitigating the mutual interference between neighboring WBANs. The interference power level, SINR, and current transmission power level are used as fuzzy inputs, and the

Table 8
Summary of game-theoretic dynamic resource management mechanisms.

Reference	Objective (improve)	Game model	Dynamic parameter	Utility function (parameters)
[77]	Inter-WBAN interference mitigation	Cooperative game (NBS)	Transmission power	SINR, emergency index, energy consumption factor
[78]	Inter-WBAN interference mitigation	Cooperative game (NBS)	Number of time slots	Network priority, channel capacity
[79]	Inter-WBAN interference mitigation	Cooperative game (NBS)	Transmission power	Criticality index, failure probability, power consumption ratio
[80–83]	Inter-WBAN interference mitigation	Non-cooperative game (Bayesian game)	Transmission power	Transmission power level, channel gain, interference factor
[84]	Inter-WBAN interference mitigation	Cooperative game (Bargaining)	Number of time slots	Channel gain
[85]	Inter-WBAN interference mitigation	Cooperative game (Contract)	Number of time slots	Channel gain
[86]	Inter-WBAN interference mitigation	Cooperative game (Auction)	Number of time slots	Channel gain

transmission power level is derived as the fuzzy output. According to the fuzzy inference rule, the proposed FLS recommends a low transmission power level when the interference power level and SINR are high. Additionally, FLS uses the transmission power level as a feedback input to gradually optimize the fuzzy output through a GA. By fusing the evolutionary mechanism with the FLS, adaptive transmission power control is possible in each superframe period.

5.6. Game-theoretic dynamic resource management schemes

In a decentralized network such as a multi-WBAN environment, game theory is considered an appropriate analytical model for handling coexistence issues. In the game-theoretic model, a group of players participates in the game and select cooperative or non-cooperative strategies to achieve better results. That is, the resource allocation problem between coexisting WBANs can be formulated as a cooperative or non-cooperative game model.

In a cooperative game, all players (i.e., coexisting WBANs) consider fairness and Pareto optimality (i.e., a condition in which it is impossible for one player to gain unilateral profits without penalizing others) for resource allocation. With a collaborative approach based on fair means, all players can achieve optimal performance of the entire network. The representative model of a cooperative game is the Nash bargaining solution (NBS). In NBS, the objective of each player is to maximize the utility function through cooperation with other players, and minimize their utility (termed disagreement point). The utility function is an indicator for evaluating the strategy selected by the players, and consists of a combination of cognitive metrics. In addition, the utility function of each player also includes the cognitive metrics of other players, allowing cooperative strategy modification. The outcome of the bargaining solution should satisfy four axioms: Pareto efficiency, symmetry, independence of linear transformation, and independence of irrelevant alternatives.

In a non-cooperative game, all players compete to maximize their profits by modifying their strategy, and ultimately all players will have a specific strategy that provides the highest rewards. The concept of the Nash equilibrium is used to determine the best solution in a non-cooperative game. In a Nash equilibrium, no players can unilaterally deviate from their strategies to improve their utility. The method of determining the Nash equilibrium is as follows. The participants of the game first mark a specific strategy that maximizes the payoff corresponding to actions of each player. Then, all players select the best strategy after detecting the strategies of the other players. However, if a participant has incomplete information regarding an opponent, the best strategy cannot be determined because the best response of the opponent cannot be predicted. In this case, a Bayesian game can be used when there is incomplete information about the interests of the opponent in the distributed game model. In a Bayesian game, player information is represented as a type, and each player adopts a different strategy for each type to maximize his/her rewards. That is, each player selects an optimal strategy according to the type-contingent best response of the other players. Table 8 summarizes game-theoretic resource management mechanisms.

5.6.1. Dynamic TPC mechanism based on cooperative games

Wang et al. [77] proposed a dynamic TPC scheme to ensure various QoS requirements of coexisting WBANs. The proposed scheme dynamically adjusts transmission power to mitigate the mutual interference between coexisting WBANs, and ensures Pareto efficiency through NBS. The utility function uses the strategy (i.e., transmission power level) of the players (i.e., coexisting WBANs) and considers three parameters: SINR, emergency index, and energy consumption factor. Each WBAN attempts to maximize the utility function with minimum transmission power, and cooperatively reduces its transmission power according to the emergency index of the neighboring WBANs, ensuring the minimum utility requirements (i.e., disagreement point). The outcome of the bargaining solution is approximated using the Lagrange multiplier method. For example, if the data sensed by an interfering node j are abnormal (i.e., node j has a larger emergency index), the coordinator cooperatively reduces the transmission power to mitigate the interference with node j. That is, the NBS determines the optimal transmission power that maximizes SINR and energy efficiency in every superframe period through the utility function, and cooperatively adjusts transmission power by considering the emergency index of adjacent WBANs.

5.6.2. Dynamic scheduling algorithm

Wang et al. [78] proposed a dynamic slot allocation algorithm to improve the network QoS in a coexisting-WBAN environment. The proposed scheme models the capacity allocation problem between coexisting WBANs as a cooperative game, in which the WBANs determine their strategies through NBS. That is, the proposed scheme satisfies the minimum capacity of each WBAN and then distributes the additional network capacity through a bargaining process, thereby improving the overall network QoS. To this end, the utility function considers network priority and channel capacity. WBANs with low priority cooperatively reduce their network capacity until the outcome derived through the utility function reaches the disagreement point.

Das et al. [84] proposed a bargaining-based optimal slot sharing algorithm to mitigate channel interferences. The proposed scheme considers the multiple performance parameters, namely, packet generation rate, buffer capacity, and transmission ratio to evaluate the utilities of each WBAN. Specifically, each WBAN participates the bargaining game for slot negotiation. Each participant places their respective demands of minimum number of timeslots in the superframe and seeks for a mutually beneficial timeslot arrangement based on the utilities. Since the participants have own minimum demand for spectrum allocation, they do not cooperate in the game below their respective minimum demand.

Bishoyi et al. [85] proposed a contract game-based priority-aware timeslot scheduling scheme to provide a differentiated QoS for critical data in multi-WBAN environment. The authors point out that providing a differentiated QoS for critical data is a challenging task in multi-WBAN environment because the data priority is a private information to each WBAN. To address this problem, the proposed scheme chooses the WBAN user with good internet connectivity as a gateway user. The gateway WBAN helps adjacent WBAN users with poor internet connectivity to forward their data to the remote server. Specifically, the

Table 9
Summary of DRL-based dynamic resource management mechanisms.

Reference	Objective (improve)	State set	Action set (dynamic parameter)	Reward function (parameters)
[87]	Inter-WBAN interference mitigation	SINR, interference power, transmission power	Transmission power	Channel capacity, normalized transmission power
[88]	Inter-WBAN interference mitigation	Nash equilibrium	Transmission power	Channel capacity, normalized transmission power
[89]	Differentiated QoS	Sum rate, response time	Number of time slots	Average delay, sum rate, response time
[90]	Energy efficiency	Data length, energy queue length	Transmission mode, relay node, number of time slots, transmission power	Energy consumption ratio
[91]	Energy efficiency, differentiated QoS	SINR, priority, battery level, delay	Access time, transmission power	Energy consumption, delay, priority, SINR
[92]	Inter-WBAN interference mitigation	Nash equilibrium	Operating channel	Achieved data rate, maximum achievable data rate
[93]	Energy efficiency	Path loss, data quantity, remaining energy	Number of time slots, transmission power	Energy efficiency, system delay, system fairness index
[94]	Inter-WBAN interference mitigation	SINR, link capacity, transmission power level	Transmission power	Link capacity
[95]	Differentiated QoS, Energy efficiency	User priority, SINR, energy consumption ratio	Number of time slots	Maximum throughput

authors model the economic interaction between the gateway WBAN and requesting WBAN users using the contract theory. The requesting WBAN users are categorized according to their data priority. Then, a contract design problem is formulated to maximize the payoff of gateway WBAN user while satisfying the requirements of requesting WBAN users.

Bishoyi et al. [86] proposed an auction-based distributed resource allocation scheme for collaborative data transmission in multi-WBAN environment. Because the utility function of each WBAN is a private information, the authors tried to solve the optimization problem using an auction mechanism. In the proposed mechanism, each WBAN users act as both auctioneer and bidder. The auctioneer initiates the auction by notifying the amount of spectrum resource it wants to share and its price. The bidder then proposes its bid to the auctioneer based on its demand. The proposed algorithm repeats the above procedure until the utility of each WBAN reaches a Nash equilibrium.

5.6.3. Cooperative dynamic bit rate adaptation

Mistra et al. [79] proposed a dynamic data-rate tuning mechanism to increase the network QoS. The proposed scheme assumes that m sensors participate in a bargaining process in an intra-WBAN environment. The utility function considers the criticality index, failure probability, and power consumption ratio. The coordinator tunes the data rate of the ith sensor at time $t+1$ according to the outcome of the utility function. For example, given the available channel capacity, a node with a low failure probability and power-consumption ratio obtains high utility (i.e., high data rate), and cooperatively reduces the data rate according to the criticality index of the neighboring nodes.

5.6.4. Non-cooperative dynamic TPC mechanism

Zou et al. [80] proposed a dynamic TPC scheme for inter-WBAN inference mitigation. The proposed scheme operates in a completely distributed manner and does not require any control message passing between WBANs. Owing to the incomplete information between WBANs, the power control problem can be modeled as a Bayesian game. Each WBAN attempts to maximize the payoff according to its utility function. The transmission power, channel gain, and interference factor are the parameters of the utility function. Given the available set of transmission power levels, each WBAN determines the best output power according to the possible actions of the coexisting WBANs, and proves that at least one unique Nash equilibrium point exists. A similar concept was considered in [81–83].

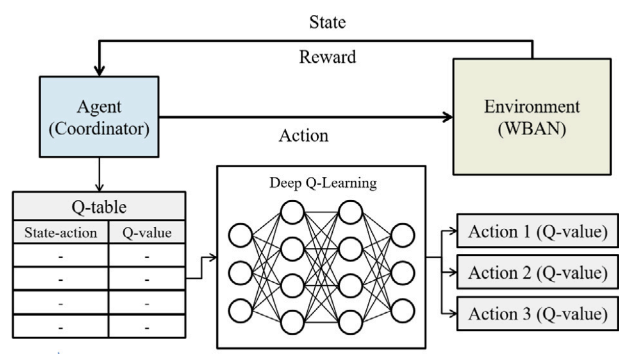


Fig. 10. Basic structure of DRL model.

5.7. Dynamic resource management schemes based on Deep Reinforcement Learning

Reinforcement learning is used to jointly optimize dynamic resource parameters through iterative experiences. It treats the problem as a model-free MDP and transforms the optimization into the maximization of the average reward of the MDP. A DRL model randomly samples the training data obtained through reinforcement learning (RL) and uses them for mini-batch training of the NN.

The representative model of RL is Q-learning. As shown in Fig. 10, the agent (i.e., coordinator) interacts with the environment (i.e., WBAN) and receives instant feedback as a reward for the result of resource allocation. Given a state that can identify the current network condition and a set of possible actions, the agent probably exploits the action with the largest cumulative sum of future rewards using the Q-function, or randomly explores the other actions to determine the optimal policy. The Q-learning process is conducted in units of episodes. In the DRL model, the optimal action for each state is stored in the replay memory and is sampled according to the uniform distribution. Although consecutive samples exhibit high correlation, this method can reduce variance because samples are randomly selected for deep learning. Table 9 summarizes DRL-based resource management mechanisms.

5.7.1. Dynamic TPC mechanism

Kazemi et al. [87] proposed a dynamic TPC scheme to mitigate inter-WBAN interference. In the proposed scheme, agents (i.e., coexisting WBANs) use Q-learning to determine the optimal transmission power level through iterative experiences. The proposed Q-learning model defines the state to identify the current network condition through three cognitive parameters: SINR, interference power, and transmission power. The possible action for each state is the transmission power level, and each WBAN attempts to determine the action with the largest cumulative sum of future rewards derived through the Q-function (i.e., reward function) during a given episode. The Q-function considers the channel capacity and normalized transmission power. Each coordinator selects an action using the ϵ-greedy algorithm. With probability ϵ, the coordinator randomly selects one action from the possible actions (i.e., explore) or selects the best action (i.e., exploit) with probability $1-\epsilon$. ϵ is called the exploration rate and gradually decreases over the processing period, assisting WBANs in determining the optimal transmission power level through iterative experiences.

Kazemi et al. [88] proposed a power control game model that uses RL to mitigate the interference between WBANs. The authors argue that existing transmission power schemes based on non-cooperative game models attempt to determine the Nash equilibrium based on predefined strategy information that may no longer be valid in a dynamically changing WBAN environment. To overcome this limitation, the proposed scheme attempts to find the Nash equilibrium using the transmission power level and SINR without information exchange between WBANs. The proposed RL model adopts the transmission power level as possible actions. The reward function considers the channel capacity and normalized transmission power. Each WBAN defines the Nash equilibrium as a terminal state, and then determines the optimal transmission power that maximizes future rewards through iterative experiences.

He et al. [94] proposed a DQN-based distributed power optimization algorithm to mitigate channel interferences. The proposed power controlling scheme is modeled as a multi-agent problem, which is implemented by distributed coordinators. The state space is defined as a set of SINR, link capacity, and transmission power level of coordinator. To adapt the dynamics of channels, each node takes actions to adjust their transmitting power during the communication process. A logarithmic equation is applied to design the reward function. Each coordinator uses Q-learning to find an optimal transmission power level that maximizes the link capacity and learns a power control policy from the WBAN environment using a DQN model.

5.7.2. Dynamic scheduling algorithm

Chowdhury et al. [89] proposed a dynamic scheduling algorithm to improve the network QoS. The proposed scheme uses Q-learning to determine the optimal scheduling policy through iterative experiences. The proposed RL model defines the state as a combination of the sum rate and response time. The action set is defined as the number of time slots assigned to each node. The future cumulative reward for each action is calculated based on the average delay, sum rate, and response time. When the coordinator performs a new resource allocation using the ϵ-greedy algorithm, it obtains the sum rate and response time from the nodes, and updates the state and Q-value. However, the number of states for possible actions increases exponentially as the number of nodes increases. To address this limitation, the proposed scheme divides the state into four levels according to the range of the sum rate and response time for fast convergence of the learning algorithm.

Kim et al. [95] proposed an adaptive scheduling algorithm to achieve multi-objective optimization. The authors point out that existing approaches have difficulty solving diverse multi-objective optimization problems in dynamic and heterogeneous WBANs because they require a prior preference of the decision makers or they are unable to solve non-discrete optimization problems. The proposed scheme consists of two parts: scheduling order optimization and the auto-scaling of relative importance. With the former, the coordinator logically integrates the decision criteria using the MCDM method and then optimize the scheduling order. For the latter, the coordinator adaptively adjusts the scales of the relative importance among the decision criteria based on the network conditions using the DQN.

5.7.3. Dynamic channel selection algorithm

George et al. [90] proposed a dynamic channel selection algorithm to mitigate inter-WBAN interference. The authors argue that the IEEE 802.15.6 channel hopping algorithm randomly changes the operating channel, resulting in a sharp performance degradation when the number of available channels is smaller than the number of coexisting WBANs. The proposed scheme models the channel selection problem between coexisting WBANs as a non-cooperative game, and uses RL to determine the Nash equilibrium. The coexisting WBANs selfishly maximize their payoff by hopping the operating channel. Each WBAN selects an action (i.e., channel selection) using the ϵ-greedy algorithm, and the reward for this action is obtained through the achieved data rate. The Nash equilibrium is defined as a terminal state, that is, each WBAN determines the optimal policy through repeated experiences until the reward for the action reaches the Nash equilibrium point.

5.7.4. Joint optimization algorithm

Chen et al. [91] proposed a joint optimization algorithm to improve energy efficiency and network QoS. To prevent packet loss and resource waste owing to frequent body movements, the proposed scheme optimizes the transmission power and time slot allocation using Q-learning. In the proposed RL model, a set of cognitive parameters, namely, SINR, priority, battery level, and delay, are used to define the current network state, and access time and transmission power are randomly allocated to the nodes using the ϵ-greedy algorithm. The reward for an action is derived through the Q-function, in which multiple metrics, namely, energy consumption, delay, priority, and SINR, are considered. The proposed scheme determines the optimal resource allocation policy (i.e., Q-table) for each state through iterative experiences. Then, the Q-table is used as a training parameter of the convolutional neural network (CNN). Similar concepts were considered in [92,93].

6. Discussions and future research directions

As the considered approaches have their own use cases in WBANs, it is difficult to define their strengths and weaknesses on a general basis. Therefore, we propose a guideline for evaluating the effectiveness of dynamic resource management techniques:

- **Adaptability:** If radio resources are statically allocated to nodes, then energy and bandwidth can be wasted at some nodes owing to dynamic characteristics of WBANs. That is, we should evaluate whether the proposed techniques are self-adaptive under dynamic network conditions (e.g., frequent body movements, heterogeneous traffic flow, and inter-WBAN interference).
- **Automation:** It is important to evaluate whether the proposed techniques can be applied in a completely distributed manner that does not require any information exchange between a coordinator and sensors or between WBANs. The addition of a new sensor in an intra-WBAN environment or the joining of a new WBAN in the local network can affect network performance. Therefore, the proposed techniques should be able to adaptively respond to changes in the external network state without modifying their algorithms.
- **Algorithm complexity:** It is necessary to evaluate whether the proposed techniques require additional status information. The coordinator has sufficient computing power and energy, whereas the sensors have limited resources. If the proposed techniques require an operation for collecting control information in addition to the sensing function, the residual energy of the sensor will be consumed quickly.

Adaptability, automation, and algorithm complexity are essential factors in the evaluation of the effectiveness of dynamic resource management techniques. As described above, the heuristic approach has various use cases, and its advantages and limitations are clearly

Table 10
Comparison between analytical models for dynamic resource management.

Analytical model	Use case	Main consideration	Adaptability	Automation	Complexity
Evolutionary Algorithm	Resource optimization	Damage to body tissue, inter-WBAN interference	Medium	Medium	High
Graph Coloring	Resource sharing	Inter-WBAN Interference	Low	Medium	Low
MCDM	Prioritization of alternative	Frequent body movement, heterogeneous traffic flow, inter-WBAN interference	Medium	Low	Medium
Fuzzy theory	Awareness of network condition	frequent body movement, heterogeneous traffic flow, inter-WBAN interference	Medium	Low	Medium
Game Theory	Resource sharing	Inter-WBAN Interference	Low	High	Medium
DRL	Joint resource optimization	Frequent body movement, heterogeneous traffic flow, inter-WBAN interference	High	High	High

indicated. Except for the heuristic approach, a comparison between other analytical models is presented in Table 10.

Evolutionary algorithms are primarily used for transmission power optimization through repetitive operation and immediate feedback. This model iteratively optimizes the target parameter until satisfactory performance is achieved. However, owing to its functional complexity, it is used for routing path optimization rather than dynamic resource management. In graph coloring, coexisting WBANs act adaptively according to predefined rules so that a given resource may not be used at the same time. Although this model has low complexity, it is used to achieve a single goal (i.e., inter-WBAN interference mitigation) rather than defining multiple functional operations. Multi-criteria decision-making allows the selection of the best alternative by using evaluation criteria for recognizing the network condition; however, it increases the overhead for collecting various cognitive metrics. In addition, as the priority of the alternatives is determined according to the preferred scale defined by the decision-maker, adaptive decision-making may not be possible owing to the bias of the decision-maker in a situation where the network condition is frequently changed. Fuzzy theory can determine the order of resource allocation after the network condition is recognized by expressing the degree of cognitive metrics using linguistic expressions. However, as the fuzzy inference rule is defined based on a series of conditional statements (i.e., if-then), adaptive decision-making cannot be made for undefined conditions. Game theory and DRL are used to define self-organizing and decentralized systems. As these models do not require any control-message passing, the resource allocation strategy can be adaptively modified according to changes in the network environment without modifying the underlying algorithms. However, these models have increased complexity, as they require constant observation and corrective actions.

Despite the functional complexity of DRL models, they are regarded as the most promising analytical models for dynamic resource management because of their self-adaptive and self-organizing properties. However, as the ϵ-greedy algorithm used in RL is probabilistic, important body data may be lost owing to a rapid performance decrease in the initial learning phase. To ensure the minimum performance in the initial learning phase, it is necessary to study the combination of RL and a heuristic resource allocation algorithm that can more reasonably compose a state–action set. In addition to DRL, deep learning can be used to extract features from personal networks and then improve the performance of the resource management scheme. For example, deep learning heuristic resource management schemes operate adaptively after predicting the sampling frequency of biosensors [96,97] or upcoming channel conditions [98,99]. That is, various dynamic resource management techniques can be developed by using unique WBAN features or patterns extracted through deep learning.

The coordinator has more resources than sensors have, but does not have sufficient processing power and energy to load NNs. To overcome this limitation, lightweight deep learning or edge computing can be applied to WBANs [100]. Lightweight deep learning allows existing deep NNs to extract the same number of features by using fewer parameters. Lightweight deep learning algorithms in CNNs are extensively studied, and research on lightweight deep learning WBAN architectures is also required. Edge computing WBAN architectures [101] allow the coordinator to transmit training data to an edge server, where complex operations can be performed. In addition, edge computing enables resource sharing in public areas without a centralized coordinator. The coexisting WBANs transmit their own data priority and control information to the edge server and receive coordinated scheduling information or transmission power level. As deep learning resource management techniques are not mature, various optimization methods and technology development are required for the application of these technologies in real life.

7. Conclusions

The mobility characteristics of the human body have led to the inherent limitations of static resource management in WBANs, leading to the development of dynamic resource management techniques. In this paper, we presented unique characteristics of WBANs and investigated state-of-the-art dynamic resource management schemes. For better understanding, we described dynamic WBAN scenarios in which performance fluctuations occur, and we clarified the target parameters to be optimized. Recent studies tend to optimize the available resources using different types of analytical models, and it is conceivable that understanding the purpose and functional behavior of analytical models can facilitate the development of optimal resource management strategies. Therefore, we classified the analytical models applicable to dynamic resource management, and we clarified their characteristics and use cases. Finally, we identified a series of research challenges.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This research was supported by an Institute for Information & Communications Technology Planning & Evaluation (IITP), South Korea grant funded by the Korean government (MSIT) (No. 2022-0-01200, Training Key Talents in Industrial Convergence Security) and Research Cluster Project, R20143, by Zayed University Research Office, UAE.

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Beom-Su Kim received B.S and M.S degrees in software engineering from Gyeongsang National University, Korea, in 2016 and 2018, respectively. He received Ph.D. degree (2022) from Chungnam National University, Daejeon, Korea. He is currently working at Chungnam National University as a postdoctoral researcher. His research interests include ad hoc networks, wireless body area networks, machine learning, and mobile edge computing.

Babar Shah is Associate Professor at the College of Technological Innovation, Zayed University, UAE. Dr. Babar received M.S degree (2007) from University of Derby, Ukand and Ph.D. (2014) from Gyeongsang National University, South Korea. Dr. Babar professional services includes but are not limited to — Guest Editorships, University Services, Workshops Chair, Technical Program Committee Member, and reviewer for several international journals and conferences. He has authored over 50 scientific research articles in prestigious international journals and conferences. His Research interests include WSN, WBAN, IoT, Churn Prediction, Security, Real-time communication and Mobile P2P networks.

Ting He is an Associate Professor in the School of Electrical Engineering and Computer Science at Pennsylvania State University, University Park, PA. Her work is in the broad areas of computer networking, network modeling and optimization, and machine learning. Dr. He is a senior member of IEEE, an Associate Editor for IEEE Transactions on Communications (2017–2020) and IEEE/ACM Transactions on Networking (2017–2021), a TPC Co-Chair of IEEE ICCCN (2022), and an Area TPC Chair of IEEE INFOCOM (2021). She received multiple Outstanding Contributor Awards from IBM, multiple awards for Military Impact, Commercial Prosperity, and Collaboratively Complete Publications from ITA, and multiple paper awards from ICDCS, SIGMETRICS, ICASSP, and IEEE Communications Society.

Ki-Il Kim received the M.S. and Ph.D. degrees in computer science from the Chungnam National University, Daejeon, Korea, in 2002 and 2005, respectively. He is with Department of Computer Science and Engineering, Chungnam National University, Daejeon, Korea. Prior to joining, he has been with the Department of Informatics at Gyeongsang National University since 2006. His research interests include machine learning for networks, wireless/mobile network, fog computing, MANET, QoS in wireless network, multicast and sensor networks.