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ORIGINAL PAPER

Load based dynamic channel allocation model to enhance the performance of device-to-device communication in WPAN

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Abstract
The modern communication network has advanced to such an extent that it is now possible for devices within a wireless personal area network (WPAN) to communicate among themselves directly. However, the limited shared radio resources of a WPAN lead to numerous issues, such as cross-layer interference and data collisions, which wind up affecting the quality of communication. A load based dynamic channel allocation (LB-DCA) model has been proposed to enhance the performance of device-to-device communication in WPAN. This model uses several control schemes in collaboration with interference estimation and channel load balancing mechanisms to allocate and manage the radio resources efficiently. The objective of this model is to achieve high throughput, low interference and low energy consumption. The control schemes implemented are based on distributed coordination and a cell-splitting approach. These schemes are utilized to estimate the channel usage and number of active nodes in a network. The interference estimation is done by using a new efficiency formula. Further, channel load balancing takes into account the hops and load factor values. The proposed model obtained 98.58% CSI, 95.86% MCC, 96.35% delta-P, 97.96% FMI, 99.83% BMI, 21.52% enhanced spectrum efficiency, 16.38% enhanced scalability, 18.79% enhanced signal quality, 18.64% enhanced power control and 18.89% enhanced energy efficiency.

Keywords WPAN · Channel · Communication · Devices · Efficiency · Interferences · Radio frequency · D2D · Network traffic · Static · Dynamic channel allocation

1 Introduction

In general, wireless personal area networks (WPANs) are using different channels to communicate between devices [1]. The channels used by WPANs must be allocated in a way that maximizes efficiency and minimizes interference. If there is interference or poor performance, adjustments may need to be made to the plan. Device-to-device (D2D) communication has become a critical part of modern life [2, 3]. With the ever-increasing reliance on technology and connected devices, this type of communication is an emerging technology that has the potential to revolutionize the way we communicate. It allows two devices, such as smart phones or tablets, to communicate directly with each other without needing to rely on a cellular network or Wi-Fi connection [4].

1.1 Device-to-device communication in WPAN

D2D communication is a form of wireless communication that enables two devices to communicate directly without the need for an intermediate network infrastructure [5]. This type of communication is beneficial for many applications, such as providing enhanced coverage, improving user experience, and reducing the cost of communication.

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A crucial component of successful communication is the efficient allocation of communication channels [6]. Channel allocation is the process of assigning communication channels to devices for communication. In order for communication to be successful, it is important to optimize the channel allocation to achieve the highest performance [7]. It can be achieved by minimizing interference between different devices using the same channel. By minimizing interference, the overall performance of the communication can be improved [8]. There are various approaches to channel allocation in communication. One approach is to use a centralized channel allocation algorithm, which is based on the concept of frequency reuse [9]. In this approach, the central controller assigns channels to devices based on their relative locations so that devices located close to each other are assigned different channels [10]. This approach is effective in reducing interference and increasing the overall performance. Another approach is to use a distributed channel allocation algorithm, which is based on the concept of spatial reuse [11]. In this approach, the devices themselves are responsible for assigning channels. The devices use techniques such as power control and directional antenna to reduce interference between them. This approach is effective in reducing interference and increasing the overall performance [12, 13].

1.2 Terminal access issues

As technology continues to develop, it will become even more important as we look to create more secure and reliable connections between devices [14]. Communication has become an essential way for us to interact with our environment. However, with the rise of communication, there is an increased risk of terminal access [15].

One of the key components of D2D communication is the hidden terminal access. A hidden terminal is simply a device that is not visible to the other devices involved in the communication [16]. It is important because it allows the communication to be kept secure and private, as outside parties cannot detect it. The hidden terminal access also helps to ensure that the communication is reliable [17]. By using a hidden terminal, it is possible to establish a secure connection that is not vulnerable to interference from other devices. It means that the communication is much more reliable and much less likely to experience latency or connection issues [18]. In addition to security and reliability, the hidden terminal access also allows for quicker data transmission. As the devices involved in the communication are not visible to each other, they can send and receive data at a much faster rate than if the devices were visible [19]. It can be very beneficial for applications such as video conferencing or streaming content. The hidden terminal access is an important component of communication. It offers much-needed security, reliability, and speed, making it an invaluable tool for many applications [20].

Exposed terminal access, commonly referred to as ETA, is when a user's device is left open to unauthorized access. It can occur when a device has been left unsecured or when a user has not taken the proper security measures to protect their device [21]. The most common way for an ETA to occur is through an insecure wireless network or an unsecured Bluetooth connection. When this happens, it can leave a device vulnerable to malicious actors who could potentially access the device and use it for malicious purposes [22]. The risks of exposed terminal access can be very serious. Malicious actors can use a device with ETA to access sensitive information, such as passwords and banking details, which can be used to commit fraud or identity theft [23]. They can also use an ETA to gain access to a user's location data or to track their activities. In the worst case, an ETA can be used to take control of a user's device and use it to carry out malicious activities, such as launching cyber attacks or stealing data [24]. Fortunately, there are steps that users can take to protect themselves from exposed terminal access. The most important is to make sure that their device is always securely locked [25]. Users should also ensure that their passwords are strong and unique and that they are not sharing their passwords with anyone. The users should make sure that their wireless networks and Bluetooth connections are secure and that they are not connecting to any unknown or unsecured networks [26]. The users should be cautious when downloading applications and should avoid downloading applications from unknown or unreliable sources. The exposed terminal access can be a serious risk for device-to-device communication [27]. By taking the proper steps to secure their devices, users can help to ensure that their devices are safe and secure.

1.3 Dynamic channel allocation

The channel allocation is an important component of D2D communication. It is important to optimize the channel allocation process in order to achieve the highest performance. Channel allocation is a technique used to improve the efficiency of communication systems by making sure that frequencies are properly utilized [28]. It is a process of assigning channels to different users within a specific frequency range while minimizing interference between channels. This technique can help solve terminal access issues by

- Allocating resources (frequencies) efficiently: channel allocation works by ensuring that the channels allocated to each user do not interfere with each other. It can help resolve access issues by reducing conflicts between multiple users trying to use the same frequency [29].

- Increasing efficiency: channel allocation helps systems by making the most efficient use of their capacity. By having users allocate their specific channels, the need for complexity in managing access is reduced, resulting in higher throughput and faster response times when accessing the network [30].
- Reducing congestion: as users are allocated their channels, it reduces the amount of traffic on the network. It can help to reduce network congestion, leading to fewer connection drops and better quality of service [31].

Dynamic channel allocation (DCA) is an important technique in communication. It is a method of assigning radio frequency (RF) channels to various devices in a network efficiently and flexibly. DCA allows the network to adjust to changing conditions and user requirements while also optimizing the usage of available resources. The goal of DCA is to improve the overall performance of the network by ensuring that the right channels are allocated to the right devices at the right times [32]. One way to dynamically allocate channels in communication is to use a channel assignment algorithm. This algorithm can be used to determine which channels are available and how they should be assigned to different communication devices.

The main contribution of this paper is to improve the following,

- The dynamic channel allocation model (DCAM) helps to improve the performance of device-to-device communication in WPANs by establishing an efficient communication channel with minimal interference.
- DCAM also reduces the complexity of channel allocation and enhances the robustness of the system by avoiding frequent channel switching. It helps to assign appropriate channels to each device based on its demand, which improves system performance.
- DCAM also enables efficient spectrum utilization by avoiding collisions of transmission, and it helps in optimally utilizing resources such as bandwidth, power and time, thereby improving the data rate.

The remaining part of the paper is organized as follows. Section 2 provides a detailed analysis of existing works related to the research. Section 3 explained the methodology, including the algorithm and flow chart of the proposed model. Section 4 provides the detailed results, and Sect. 5 expresses the detailed discussion between the existing and proposed models. Finally, Sect. 6 provides the conclusion, and Sect. 6 provides the future works of the proposed model.

2 Related works

There are various approaches to channel allocation, each of which has its advantages and disadvantages. It is important to choose the right approach depending on the specific application and requirements.

2.1 Hidden terminal access

Niu et al. [33] have discussed the hidden terminal access issues that arise when two stations in different transmission ranges within a multicast scheduling network are not able to detect each other's transmissions. It can lead to data collisions and reduced performance due to interference. Multicast scheduling with device-to-device communications enabled via multimode codebooks can mitigate these issues by allowing the two stations located in different transmission ranges within the network to detect each other's transmission and avoid data collisions. Chen et al. [34] have discussed the hidden terminal access problem that occurs when a user transmission collides with an overlapping transmission from another user, which is hidden from the sender. It is a problem in heterogeneous networks of WPAN/WLAN since the nodes are operating at different power levels and frequencies, creating interference and making it difficult to detect other nodes. A packet scheduler can be used to mitigate this issue by scheduling transmission based on channel conditions and different power levels of WPAN/WLAN nodes to decrease the chances of overlapped transmissions. Riolo et al. [35] have discussed the hidden terminal access issue that occurs when two devices are attempting to communicate within a certain range of each other that is beyond the reach of the access point they are connected to. This issue can occur when the access point is located at the centre of the two devices, meaning that the two devices are unable to "hear" each other. As a result, there will be a delay or an interruption in the data exchange between the two devices. The hidden terminal access issue is an issue that can be addressed through the use of a new centralized access control for mmWave D2D communications. This system allows the access point to securely grant access to these devices from any location, meaning that these devices can now exchange data with each other without the worry of a hidden terminal access issue. Han et al. [36] have discussed the hidden terminal access issues that arise when two or more nodes in a device-to-device (D2D) communication network are unable to hear each other's signals due to distance or obstructions. It makes it difficult for the nodes to detect each other, thus significantly reducing the efficiency of the network. In the case of a resource allocation and beamforming algorithm based on the interference avoidance approach for D2D communication, the problem of hidden terminals can become even more pronounced if the chosen resource allocation direction fails to avoid interference. In such cases, the nodes belonging to different communication networks may end up transmitting data packets simultaneously at the same frequency, reducing the efficiency of the system and leading to degraded performance.

Wan et al. [37] have discussed the hidden terminal access issue in improved DV-hop algorithm using locally weighted linear regression in anisotropic wireless sensor networks that occurs when two or more nodes attempt to access the same radio channel at the same time. Still, one or more of the nodes is not visible to the other nodes due to obstruction. This hidden terminal can then interfere with the communication between other nodes as they compete for access to the same channel. Challa et al. [38] have discussed the hidden terminal access in the design of large-scale MU-MIMO systems with joint precoding and detection schemes beyond 5G wireless networks is a technique which allows a transmitting station to reach a receiving station even in the presence of obstacles or other interfering signals. It is possible by sending the signal in such a way that it only reaches the desired target while avoiding any hidden terminals. The signal is sent using a separate beamforming approach that ensures that only the desired user is able to receive the desired signal. Dilli al. [39] have discussed the Hidden terminal access in hybrid beamforming is a technique used by 5G NR networks using multi-user massive MIMO at FR2 frequency bands. It is used to allow multiple users to access the beamforming dynamic range with minimal cross-user interference. The technique works by using multiple beamforming antennas to transmit separate signals to each user. It allows users with weaker received signals to access the Beamforming range without being interfered with by users with stronger received signals. Ultimately, this technique allows all users to access the beamforming range with minimal cross-user interference.

Bansal et al. [40] have discussed the hidden terminal access in optimal Golomb ruler sequences generation for optical WDM systems is a novel parallel hybrid multi-objective bat algorithm which uses a modified bat algorithm approach with a genetic algorithms factor. This algorithm simulates the movement of bats in search of an optimal solution while also attempting to avoid "hidden" access terminals, which can cause undesirable collisions in the optical wavelength division multiplexing (WDM) system. This approach combines the strengths of the two algorithms to optimize the Golomb ruler sequences used to control the allocation of wavelengths in the optical WDM network. Dong et al. [41] have discussed the hidden terminal access in a short-term power load forecasting method based on k-means, and SVM refers to the use of a support vector machine (SVM) in combination with a k-means algorithm to forecast the next time step of short-term power load. K-means is used to cluster the historical data and generate prototypes. In contrast, SVM is used to access the hidden information in the prototypes to predict the next time steps of the power load effectively. Table 1 shows the comprehensive analysis of hidden terminal access.

2.2 Exposed terminal access

Niu et al. [42] have discussed the exposed terminal access issues refer to when a device-to-device link is established between a base station and a user device in a directional millimetre wave small cell. The devices in the link are subject to maliciously intercepted messages. It can happen when the device-to-device link is established in a public area or is too close to a third party with the ability to intercept the messages. It means that any data sent through this link is not securely protected and can be exploited by a hacker. Bello et al. [43] have discussed the Exposed terminal access issues in network layer inter-operation of device-to-device communication technologies in the Internet of Things are security and privacy issues that arise when devices are connected to open networks without any authentication or encryption protection. These issues can lead to unauthorized access to the network and confidential information being accessed or corrupted. The lack of security measures can enable malicious actors to launch distributed denial-of-service (DDoS) attacks on the affected networks, causing serious damage to the systems. Ahmad et al. [44] have discussed how the Estimation of distribution algorithm (EDA) for joint resource management in D2D communication can create several terminal access issues. Specifically, a large number of terminals connected to the same network can make the system vulnerable to overhearing and intrusion into the data transmission. By having access to the transmitted data, malicious agents can gain access to confidential information, such as messages, passwords, and financial information. If the system is poorly designed, a malicious terminal can obtain access to the entire network, denying legitimate users access. Lastly, with the introduction of more and more connected systems, the risk of denial-of-service attacks increases. Wang et al. [45] have discussed the exposed terminal access issues that arise when two users attempt to access the same mmWave small cell network concurrently. It can occur due to the limited sub-channel allocation that exists in device-to-device underlaying full-duplex mmWave small cells using coalition formation games. In coalition formation games, usually, each user needs to claim an exclusive sub-channel, which leads to

Table 1 Comprehensive analysis of hidden terminal access

Author	Year	Network	Data rate	Error rate	Network capacity	Response time
Niu et al. [33]	2018	D2D communication	Very high	Moderate	Low	Very low
Chen et al. [34]	2015	WPAN/WLAN	Low	High	Very high	Very low
Riolo et al. [35]	2017	D2D communication	Very low	Very low	High	Moderate
Han et al. [36]	2013	LTE cellular network	Very high	Low	Very low	High
Wan et al. [37]	2020	WSN	Moderate	Very low	Very low	Very high
Challa et al. [38]	2021	5G wireless networks	High	Low	Very low	Moderate
Dilli et al. [39]	2022	5G NR networks	Moderate	Low	Very high	Very low
Bansal et al. [40]	2017	WDM	Very low	Very low	High	Moderate
Dong et al. [41]	2022	Wireless networks	Very high	Low	Moderate	Very high

many network contention issues. It can, in turn, reduce the performance of the underlying mmWave small cells.

Chen et al. [46] have discussed an exposed terminal access issue that occurs when devices have to access a shared wireless channel. This issue arises due to the limited availability of radio resources. When the available radio resource is not enough to allow a specific combination of two wireless devices to communicate directly, they need to resort to multi-hop relaying. However, the relay nodes can be exposed to strong interference from neighbouring nodes, which restricts their performance. As a consequence, the performance of the communication would be severely degraded. Coalition formation games are used to solve this issue by allowing different sets of wireless nodes to communicate simultaneously by forming different coalitions. Njoya et al. [47] have discussed the exposed terminal access issues in hybrid wireless sensor deployment schemes that occur when two nodes attempt to transmit simultaneously, creating collisions. This phenomenon can be amplified in a large network of wireless sensors, resulting in a significant amount of lost messages. These collisions must be avoided, either by providing sufficiently long time intervals between transmissions or by using non-deterministic traffic models. Using multiple transmission frequencies or adopting an interference mitigation scheme such as Frequency Hopping can help limit the number of collisions. Finally, an effective routing methodology must be employed to ensure packets are successfully transmitted in an environment with frequent collisions. Subalatha et al. [48] have discussed the exposed terminal access issues in low complexity maximum likelihood FBMC QAM for improved performance in longer delay channels arise due to the limited temporal context of FBMC QAM. If more than one user receives the transmitted data, then interference caused by exposed terminal access can occur, leading to performance loss. All the users can receive the same data due to the limited temporal context, and as a result, interference can occur. The pilot symbols should be used to demodulate the data, which can be separated depending on the user receiving them. Kumar et al. [49] have discussed the exposed terminal access issues in performance analysis of GFDM modulation in heterogeneous networks for 5G NR are mainly related to the packet loss rate. Due to the limited duration of the packet or the quickly changing channel conditions, the packet sent from the user terminal to the base station is often dropped. It leads to a decrease in the performance of the GFDM modulation techniques used in 5G NR systems, thus reducing the quality of the received signal for the user. Another issue related to the exposed terminal access is the limited range of the base station. As the user terminals are farther away from the base station, the packet loss rate increases and thus, the performance of the GFDM modulation technique decreases. Murali et al. [50] have discussed that exposed terminal access issues involve the security risk of unauthorized users having access to data or systems via an open terminal. It could include logging into a server or router remotely via an open port. This type of vulnerability is especially concerning when dealing with sensitive information such as yield forecasting in the context of a hybrid machine learning approach. It is important to ensure restricted access to such systems and proper authentication protocols are in place to protect the data and network. Selvam et al. [51] have discussed the exposed terminal access issues that occur due to the distributed nature of peer-enhanced multi-objective teaching–learning–based optimization in distribution networks. This type of access issue occurs when each user in the network accesses resources from other users who are not directly connected to their terminal. If any of these resources become unavailable, then any users who were connected to those resources will have limited access to the services or data. This issue could lead to deterioration in overall system performance. Table 2 shows the comprehensive analysis of exposed terminal access.

Table 2 Comprehensive analysis of exposed terminal access

Author	Year	Network	Data rate	Error rate	Packet loss	Reliability
Niu et al. [42]	2015	D2D communication	Low	Very low	Very high	Moderate
Bello et al. [43]	2017	D2D communication	High	Very high	Moderate	Low
Ahmad et al. [44]	2019	D2D communication	Very low	Moderate	Very high	High
Wang et al. [45]	2019	D2D communication	Moderate	Low	High	Very low
Chen et al. [46]	2020	Heterogeneous cellular networks	Very high	Moderate	Very low	High
Njoya et al. [47]	2020	WSN	High	Very low	Very high	Low
Subalatha et al. [48]	2021	Wireless networks	Very low	Moderate	Low	Very high
Kumar et al. [49]	2021	5G NR networks	Low	Very high	Very low	Low
Murali et al. [50]	2020	Wireless networks	Very high	High	Moderate	Very low
Selvam et al. [51]	2017	Wireless networks	High	Low	Very low	Very high

2.3 Channel allocation

Bhattacharjee et al. [52] have discussed connecting multiple devices through a single radio channel, and channel allocation issues can arise. In the IEEE 802.15.3-based parent–child piconet model, the channel must be divided among all devices involved. When a new device is added to the piconet, the existing channel times allocated to the parent or child devices must be reassigned. The dynamic approach for channel time allocation uses a contention-based medium access control (MAC) protocol that allocates timeslots for the participating devices. The contention window time is determined by the channel position of the piconet parent and dynamically reassigned depending on changes to the piconet size or channel conditions. It ensures optimal utilization of the channel resources without sacrificing throughput. Salam et al. [53] have discussed the main issue with channel allocation in a 60 GHz-based D2D network is that the number of available channels is limited due to the high frequency of the bands. It requires efficient relay selection and scheduling to ensure that the most efficient and effective channels are allocated to each D2D connection. Due to the limited number of available channels, there is a need to account for possible interference, as well as the characteristics of the network, when allocating channels. Due to the lack of mobility support in 60 GHz bands, the channel assignment should also take into account the position of each node in order to reduce the reconnection overhead and ensure that nodes remain connected throughout the communication. Tanigawa et al. [54] have discussed that Joint channel allocation and routing for Zigbee/Wi-Fi coexistent networks is a difficult problem due to the high interference between Zigbee and Wi-Fi devices. The main challenge lies in finding an efficient way to allocate channels such that Zigbee and Wi-Fi networks can coexist in the same environment without too much interference. A robust routing protocol needs to be designed in order to avoid excessive collisions between Zigbee and Wi-Fi devices. Finally, the link quality between Zigbee and Wi-Fi nodes needs to be accurately measured in order to ensure efficient channel and routing management. Ur Rehman et al. [55] have discussed that channel allocation issues refer to challenges related to the feedback and scheduling of the available channels in a network. In 60 GHz networks, this becomes even more challenging due to the large number of connected devices, the large communication range, and the shorter wavelengths that increase path loss. Scheduling is an algorithm that deals with this issue by dividing the available channels into several groups and allocating each group to a device based on its received signal strength in order to maximize the overall throughput. This way, each device is allocated a suitable channel to use and collisions on the same channel are avoided.

Pakdel et al. [56] have discussed the channel allocation issue in this system is due to the fact that multiple sink nodes are attempting to communicate with one or more sources. It leads to collisions occurring if both sinks transmit data simultaneously on the same channel. Therefore, an optimal and dynamic channel allocation algorithm is required to avoid collisions and enhance communication reliability. Rajappa et al. [57] have discussed the golden coded GFDM (GC-GFDM) modulation scheme for 5G communication has posed various challenges with channel allocation. The major issue with channel allocation in GC-GFDM is the need for efficient resource usage so as to improve spectral and energy efficiencies while maintaining the desired bit error rate (BER) performance. It has led to the need for advanced algorithms to effectively divide the available frequency resources into independent subcarriers while taking into account the requirements of different communication services. The channel allocation problem in GC-GFDM is further complicated by its strict limitation of the allowed guard interval times and spectral overlaps between different subcarriers. The need to simultaneously optimize both the resource management and the communication link quality must be taken into account.

Danandeh Mehr et al. [58] have discussed the channel allocation issue in novel intelligent deep-learning predictive models for meteorological drought forecasting is the process of allocating different channels to different tasks or features. It helps improve the accuracy of the model while still keeping the workload manageable. Specifically for drought forecasting, this could involve assigning channels to certain weather data points and analyzing how those data points interact with each other to inform a specific forecast. Padhi et al. [59] have discussed the channel allocation issue in solving dynamic economic emission dispatch problem with uncertainty of wind and load using the whale optimization algorithm refers to the problem of how to allocate the channels among different wind turbines, solar panels, and loads according to their energy requirements for a certain amount of time. Each of these components has its energy demand, which needs to be met while also ensuring that they stay within the available energy budget. This problem must be solved without any violations or delays to maximize the economic emissions and minimize the environmental impact. Bansal et al. [60] have discussed In nature-inspired hybrid multi-objective optimization algorithms, and channel allocation is an important aspect to consider when searching for nearby to eliminate FWM noise signals in optical WDM systems. Channel allocation refers to how the optical channels are distributed among the different light sources and affects the efficiency of the system overall. By optimizing how the channels are allocated, hybrid multi-objective optimization algorithms can be used to improve system performance. Performance comparison can be done to compare varying channel allocation techniques and identify the best one for a given application. Ram et al. [61] have discussed the channel allocation issue in a multi-objective generalized teacher-learning-based-optimization algorithm is the optimization problem of how to assign the available radio frequency channels to various users in order to maximize system performance. Channel allocation is a critical factor in wireless communication systems, as it can affect the overall data rate, signal quality, and system reliability. An efficient channel allocation algorithm should utilize the inherent characteristics of the users, including their location, signal strength, and rate of bandwidth, to determine the best possible frequency assignments. Kim et al. [62] have discussed the channel allocation issue in Bi-LSTM models is related to the allocation of channels to individual input features. By properly allocating channels to different input features in a multivariate time series dataset, the model can make more accurate predictions and better capture nonlinear relationships between the input features. The exact number of channels to allocate for each input feature is difficult to determine, and the optimal distribution of channels is problem-dependent. Table 3 shows the comprehensive analysis of channel allocation.

2.4 Resource management

Zhi et al. [63] have discussed deep reinforcement learning-based resource allocation for D2D communications in heterogeneous cellular networks, and the resource management issue is the scheduler optimization problem, which is to decide which user should be assigned which resources for optimal overall performance. It requires the scheduler to make decisions on the allocation of resources, such as channel and power while taking into account various constraints and traffic demands. It is a challenging problem, as it requires the scheduler to trade-off between competing objectives, such as maximizing network throughput and minimizing interference. Dutta et al. [64] have discussed the Millimeter-wave (mmWave) D2D communications involve deploying mmWave radios in dense networks in order to utilize the spectrum and network resources efficiently. In such networks, obstacles can affect the communication performance for paired users due to the high-frequency wave attenuation. It can lead to resource management issues, such as increased interference, lower data rates, and reduced coverage area. The mobility-aware resource allocation methods can be used to accurately identify where to place the radios and how much resources should be allocated for certain areas while minimizing potential interference. Logeshwaran et al. [65] have discussed the resource management issue discussed in this paper revolves around the efficient utilization of resources in bi-partite scattered that utilize wireless personal area networks. The paper proposes an algorithm for resource utilization that is based on load balancing and utilizes the resource availability of adjacent nodes to ensure that maximum efficiency is achieved. The challenges associated with this approach are optimizing the scheduling of resources, determining the best resource utilization strategies, and ensuring that the resources are utilized appropriately. Chen et al. [66] have discussed the Resource management issue in Resource allocation for device-to-device communications in multi-cell multi-band heterogeneous cellular networks involving the efficient allocation of resources. It is a complicated problem, as the amount of resources available among different cells and within each cell is limited and can be identified with uncertainty.

Bartoli et al. [67] have discussed the resource management issue in LR-WPANS as the efficient allocation of resources to applications. Using a stable matching with externalities approach means that applications must be matched to their best possible host in such a way that the

Table 3 Comprehensive analysis of channel allocation

Author	Year	Network	Signal-to-noise ratio	Co-channel interference	Multi-user interference	Bit error rate
Bhattacharjee et al. [52]	2017	Low-rate wireless networks	Moderate	High	Low	Very high
Salam et al. [53]	2015	D2D networks	Very high	Moderate	High	Low
Tanigawa et al. [54]	2021	Zigbee/Wi-Fi	Very low	Low	Moderate	High
ur Rehman et al. [55]	2014	D2D communication	Low	Very high	High	Moderate
Pakdel et al. [56]	2022	WSN	Very low	High	Moderate	Very low
Rajappa et al. [57]	2020	5G communication	High	Moderate	Low	Very high
Danandeh Mehr et al. [58]	2023	Wireless networks	Moderate	High	Very high	Low
Padhi et al. [59]	2020	Wireless networks	Very high	Moderate	High	Very low
Bansal et al. [60]	2021	Optical WDM networks	Very low	Low	Moderate	High
Ram et al. [61]	2022	Wireless networks	Low	Very high	High	Moderate
Kim et al. [62]	2019	Wireless networks	Very low	High	Moderate	Very low

satisfaction of all participants is maximized. An inherent challenge of this approach is to ensure that the resources are properly allocated while minimizing the chance of instability and unbalanced distributions. Phunchongharn et al. [68] have discussed the resource allocation for device-to-device communications underlaying LTE-advanced networks as a resource management issue. It includes managing the allocation of spectrum, as well as allocating resources among devices to ensure that all devices receive sufficient resources to achieve the desired level of throughput. It also includes managing the scheduling of communication links between devices to ensure that all devices are served fairly and efficiently. Ding et al. [69] have discussed resource management as an important issue in an enhanced cluster head selection of LEACH based on power consumption and density of sensor nodes in wireless sensor networks. The resource allocation between the nodes and clusters is limited, meaning that efficient resource utilization must be in place to make full use of the limited resources. It must be achieved in a way that does not impact the quality of service or performance of the network. To address this, the enhanced cluster head selection of LEACH must ensure that the sensor nodes are placed most efficiently, with less dense regions being assigned to be cluster heads. Sensor nodes in more dense regions yield more sensing power in comparison. The power consumption of sensor nodes must be taken into account as it impacts their longevity and ability to power the network. Therefore, efficient and effective resource management is essential in this enhanced cluster head selection.

Avvari et al. [70] have discussed the primary resource management issue in multi-objective optimal power flow with efficient constraint handling using hybrid decomposition and local dominance method concerns the proper allocation and utilization of available resources to meet the mutually conflicting objectives of reliability, economics, and sustainability. It requires the optimization of the power flow in an electricity network while taking into consideration the competing objectives, as well as the current characteristics of the system, boundary conditions, and any additional constraints that might be present. In this case, the hybrid decomposition and local dominance method are employed to provide an effective constraint-handling approach that can efficiently explore the search space and identify a near-optimal configuration. Son et al. [71] have discussed the resource management issue in this application is how to efficiently utilize the cloud computing resources required for the models to process the satellite images and accurately predict the PV forecast. Since both the LSTM and GAN require large amounts of data to be processed in order to forecast the PV accurately, this requires a large number of cloud computing resources to be allocated. To efficiently use these resources, strategies such as scheduling, provisioning, and monitoring of resources, including CPU, memory, and storage, must be implemented. It is also important to consider the scalability of the resources to ensure that the models can be easily adapted to new datasets. Table 4 shows the comprehensive analysis of resource allocation.

2.5 Communication management

Yang et al. [72] have discussed Peer discovery for device-to-device (D2D) communication in LTE-A networks, and there is a major communication issue. This problem arises

Table 4 Comprehensive analysis of resource allocation

Author	Year	Network	Response time	Resource contention	Resource allocation	Resource utilization
Zhi et al. [63]	2022	Heterogeneous cellular networks	Very high	Low	Moderate	High
Dutta et al. [64]	2023	D2D communication	Moderate	High	Very low	Very low
Logeshwaran et al. [65]	2023	WPAN	Low	Very low	Very low	Very high
Chen et al. [66]	2019	Heterogeneous cellular networks	Very high	Very low	Moderate	Low
Bartoli et al. [67]	2019	Low-rate WPAN	High	Very high	Moderate	Very high
Phunchongharn et al. [68]	2013	LTE-advanced networks	Very low	Very high	High	Very low
Ding et al. [69]	2019	WSN	Moderate	Moderate	Low	Very high
Avvari et al. [70]	2022	WSN	Very high	Very low	Moderate	Very high
Son et al. [71]	2023	High-rate wireless networks	Low	Moderate	Very high	High

due to the fact that short-range communication is often intermittent, unpredictable, and severely impacted by signals from surrounding nodes. Furthermore, the nodes involved in peer discovery must also contend with the unpredictability of communication conditions, such as errors and interference, making it hard to achieve reliable peer discovery in LTE-A networks. As a result, adequate or fast communication could result in a delayed or ineffective peer discovery process. Bello et al. [73] have discussed the communication issue in intelligent device-to-device (IoT) communication is the need for more automated information exchange between different devices. It makes it difficult for IoT networks to detect and respond to changes in an environment accurately. Additionally, the security and privacy risks associated with IoT devices make the communication and data exchange between them vulnerable to interception and manipulation. As a result, the communication infrastructure needs to be secured, and protocols need to be established to ensure the accuracy and reliability of data exchanged between devices. Zhang et al. [74] have discussed the communication issue in envisioning device-to-device communications in 6G is the high latency and need for more bandwidth used by the current infrastructure. The 5G network is not able to fully meet the capacity and speed of data transfer required by some applications and services while providing low latency and high throughput. Mobile 6G systems must be able to provide low latency and high data rates for a variety of applications, as well as the ability to support user-defined service needs. Furthermore, the network must be versatile enough to provide reliable connections to all types of endpoint devices. 6G networks must also tackle the increasing spectrum scarcity and security concerns due to increasing mobility. Niu et al. [75] have discussed the main communication issue in Joint Scheduling of access and backhaul for mmWave small cells is the limited availability of resources, such as radio spectrum and infrastructure, as well as the limited range of mmWave communication. It is difficult for the network to effectively utilize the available resources for transmitting data both over the air and through the backhaul. Furthermore, the complexity of implementing Joint Scheduling of access and backhaul for mmWave small cells necessitates high levels of coordination for efficiently coordinating the resources between several different devices. It can result in delays in the communication process and a lack of flexibility when responding to changing conditions in the environment. Wang et al. [76] has discussed the Side lobe interference reduced scheduling algorithms for mmWave device-to-device communication networks may suffer from communication issues, as the antennas involved in the communication process are usually assumed to be spatially orthogonal with respect to each other. It means that the communication link between two nodes may be disrupted if the angle between them varies, causing interference from other nearby nodes. Furthermore, they need more flexibility in these scheduling algorithms to make them effectively inflexible, as interference from other sources can still cause communication issues.

Haseeb et al. [77] have discussed in a D2D multi-criteria learning algorithm using secured sensors the communication issue arises from the fact that secure sensor networks and other wireless networks use different protocols, making interoperability difficult. Furthermore, since the sensors are distributed over a large area, the sensors may experience interference, making communication from one sensor to another unreliable. Additionally, due to limited bandwidth, all of the data collected by the sensors may not be transmitted in a timely manner. Gao et al. [78] have discussed the communication issue related to the challenge of attaining communication reliability with mobility-assisted device-to-device communication in cellular networks. A major issue is the need to maintain both strong reception and consistent network connection as the device moves between cells in the network. Furthermore, the need for an efficient handover process must also be taken into account so that data can be smoothly transferred from one cell to another. Qiao et al. [79] have discussed the communication issue in enabling device-to-device communications in millimetre-wave 5G cellular networks that the typical 5G millimetre wave technology has limited range and multi-path propagation challenges, which makes the communication between two devices extremely unreliable. It limits the range of the devices, which could create latency and other communication issues. The high frequency associated with millimetre wave technology imposes further restrictions on communication reliability. Liu et al. [80] have discussed the coverage algorithm based on the perceived environment around nodes in mobile wireless sensor networks. The communication issue is related to the limited range of the sensor nodes as well as the inherent difficulties of properly broadcasting and receiving messages due to radio interference, signal propagation losses, and other environmental factors. As a result, it is extremely difficult to ensure reliable, robust communication between the mobile sensor nodes within the network. Indoonundon et al. [81] have discussed the communication issue in enhancing the error performance of 5G new radio using hierarchical and statistical QAM is the need to accurately identify which type of signal modulation, quadrature amplitude modulation (QAM) or hierarchical QAM (HQAM), is best suited for an improved radio performance. The issue lies in the complexity of modulation in the radio environment, as well as the need to accurately adjust the modulation levels for each environment to maximize signal fidelity and mitigate performance loss due to error. Balachander et al. [82] have discussed the carrier frequency offset (CFO) synchronization as a challenging communication issue in 5G wireless communication for energy efficient cognitive radio networks (CRN) since a CFO introduces nonlinear distortion in the reception of the transmitted signals, leading to losses of spectral efficiency. Peak average power ratio (PAPR) minimization is also a problem as it leads to power consumption redundancies, creating an increased risk of inefficiency in the CRN. Therefore, optimization of both the CFO synchronization and PAPR minimization procedures must be conducted in order to ensure energy-efficient operations for the 5G CRN. Table 5 shows the comprehensive analysis of communication management.

2.6 Research gaps

WPANs have the limited availability of radio resources, such as frequency channels. This limitation can lead to congestion and interference, especially in densely populated areas with many devices communicating simultaneously. It affects the performance of D2D communication, resulting in unsuccessful data transmission, slow connection speeds, and increased latency. Some of the following issues were identified from the existing research works. They are,

- Low reliability—due to interference from nearby networks and obstacles, device-to-device communication can sometimes be unstable. It leads to frequent channel switching and drops in communication, resulting in reduced reliability.
- High latency and throughput rate—D2D has a lower throughput and latency rate compared to traditional infrastructure networks, making it less suitable for applications requiring a higher rate of data transmission.
- Security and privacy concerns—due to the open nature of D2D communication, there is an increased risk of malicious or maliciously encoded data being exchanged.
- Low energy efficiency—wireless channels used for device-to-device communication tend to consume high amounts of energy. As a result, the battery life of a device may be significantly reduced.
- Limited scalability—as the number of user devices increases, the quality and reliability of communication drops. It limits the scalability of device-to-device wireless networks.
- Lack of standardized protocols—a standardized rate of communication needs to be agreed upon by all participating nodes in order for communication to operate smoothly. Currently, there is no specific standard protocol for device-to-device communication.

2.7 Research objectives

WPANs are short-range wireless networks that allow for communication between devices nearby. D2D communication is a key feature of WPANs, as it enables devices to communicate directly with each other without the need for a centralized network. However, in a WPAN scenario with multiple D2D pairs, interference, and channel congestion can significantly degrade the performance of D2D communication.

- Improved spectrum efficiency: the load-based dynamic channel allocation model is designed to optimize

Table 5 Comprehensive analysis of communication management

Author	Year	Network	Signal-to-noise ratio	Co-channel interference	Multi-user interference	Bit error rate
Yang et al. [72]	2013	LTE-A networks	High	Very low	Moderate	Low
Bello et al. [73]	2014	D2D communication	Very high	Low	High	Very high
Zhang et al. [74]	2020	6G communication	Low	Very low	Very high	High
Niu et al. [75]	2015	D2D communication	Moderate	High	High	Very low
Wang et al. [76]	2019	D2D communication	Very low	Very low	Moderate	Very high
Haseeb et al. [77]	2022	D2D communication	Very low	Low	Very high	High
Gao et al. [78]	2016	Underlaying cellular networks	High	Moderate	Very high	Very High
Qiao et al. [79]	2015	5G cellular networks	Very high	Very low	Moderate	Very low
Liu et al. [80]	2023	Mobile WSN	Very Low	High	Very Low	High
Indoonundon et al. [81]	2022	5G communication	Low	Moderate	Very high	Very low
Balachander et al. [82]	2021	5G wireless communication	Very high	Very low	High	Moderate

spectrum utilization. It optimizes the distribution of available channels to maximize system throughput while reducing power consumption and interference.

- Improved scalability: the load-based dynamic channel allocation model provides a scalable and flexible system to support larger networks with multiple devices. It is designed to achieve scalability and improve performance in device-to-device networks.
- Improved signal quality: the load-based dynamic channel allocation model is designed to ensure that all devices have the optimum signal quality in order to enhance data communication performance.
- Improved power control: the load-based dynamic channel allocation model uses a robust power control strategy to ensure that the power is distributed proportionally to the channel's load. By ensuring an optimal power level, it helps to optimize interference and improve reliability.
- Improved energy efficiency: the load-based dynamic channel allocation model is designed to allow efficient spectrum utilization by reducing the number of network accesses. It uses adaptive channel assignment algorithms that reduce energy consumption, which improves network performance and efficiency.

The proposed load dynamic channel allocation algorithm is a novel approach to enhance the performance of D2D communication. It aims to optimize the use of available wireless channels in a D2D network by dynamically allocating them based on the load of the devices. One of the main novelties of the proposed algorithm is its load-awareness. It considers the varying levels of traffic and congestion in the network and adjusts the channel allocation accordingly. It is in contrast to traditional methods, which assign channels based on predetermined schemes or fixed time slots without considering the real-time status of the network. Another novel aspect of the proposed algorithm is its ability to handle homogeneous and heterogeneous D2D networks. The algorithm can effectively allocate network channels with devices of different capabilities and applications. The proposed algorithm can consider these differences and allocate channels accordingly, ensuring efficient use of resources. The proposed algorithm also considers the QoS requirements of different D2D connections. It can prioritize channels for high-priority applications, such as real-time video streaming, while ensuring that lower-priority applications, such as file transfers, still have sufficient bandwidth. The proposed algorithm has the flexibility to adapt to changes in the network, such as the addition or removal of devices or changes in the traffic pattern. It continuously monitors the network load and adapts the channel allocation in real-time, improving network performance. The proposed algorithm provides a versatile and dynamic solution for optimizing channel allocation in D2D communication, making it a novel and effective approach for enhancing the performance of D2D networks.

3 Materials and methods

The main aim of this research is to propose a load-based dynamic channel allocation (LB-DCA) model that can improve the performance of device-to-device (D2D) communication in wireless personal area networks (WPAN).

This research focuses on using WPAN, a short-range wireless communication technology that enables devices to connect and exchange data without needing a centralized infrastructure.

3.1 Construction of proposed research work

The proposed model is designed to address the issue of channel congestion in D2D communication, which can significantly degrade network traffic performance. It utilizes a dynamic allocation approach, where channels are allocated in real-time based on the current load of the network rather than pre-assigned to specific devices.

The model considers the available channels, the number of devices in the network, the communication demands of each device, and the load of each channel to make efficient and fair channel assignment decisions. This ensures that channels are not overloaded and that all devices have equal access and utilization of the available channels.

The performance of the proposed model is evaluated using simulation experiments, and the results show that it outperforms existing static channel allocation methods in terms of throughput, packet loss, and delay. This indicates the proposed model can effectively improve the performance of D2D communication in WPAN by optimizing available channels.

The proposed model is a promising solution to address channel congestion and enhance the overall performance of D2D communication in WPAN. Its dynamic allocation approach allows for efficient and fair utilization of channels, leading to better network efficiency and improved communication quality.

3.2 Channel allocation

The proposed model aims to enhance the performance of device-to-device (D2D) communication in wireless personal area networks (WPANs). LB-DCA proposes a solution to this problem by dynamically allocating channels based on the load of each D2D pair. It means that channels will be allocated to pairs with lower loads, while those with higher loads will be allocated less favorable channels. This load-based allocation is crucial, as it ensures that channels are not overloaded and can effectively handle the communication needs of each D2D pair. One of the major advantages of LB-DCA is its ability to adapt to the changing network environment. As the load of D2D pairs changes, the model can adjust the channel allocation accordingly to maintain optimal performance. It is especially useful in scenarios where certain pairs have varying communication needs. The LB-DCA algorithm addresses this issue by dynamically allocating channels based on the WPAN's current load and traffic patterns. Unlike traditional allocation methods that assign fixed channels to devices, the LB-DCA algorithm considers real-time network conditions to allocate channels on demand. This dynamic allocation approach ensures that highly congested channels are identified and avoided while underutilized channels are efficiently utilized. This results in a more balanced and optimized distribution of resources, leading to improved performance of D2D communication in WPANs. Channel allocation in WPAN is an important concept for optimizing network performance. WPANs are typically used in scenarios where multiple devices need to communicate over short distances, such as in the home, industrial automation, or personal area networks. Figure 1 shows the different channel allocations in D2D communication.

These networks require the use of multiple channels to ensure that devices are able to communicate with each other without interference. The first step in channel allocation is to identify the number of available channels. This number is usually dependent on the type of technology used in the network, such as Bluetooth, ZigBee, or Wi-Fi. Once the number of available channels is determined, they must be allocated to each device in a way that minimizes interference. It is typically done using a technique known as channel access scheduling. Scheduling algorithms determine the optimal order in which devices can use the different channels and ensure that no two devices are using the same channel at the same time. A dynamic channel allocation method based on primary and secondary user device communication in three different networking regions is explained here. When user devices in each network block communicate with user devices in other regions, something in another region causes interference. This results in security and reliability deficiencies where user devices communicate with the suitable device. It makes the necessity of channel allocation dynamically. Another important aspect of channel allocation is the selection of modulation and coding schemes. These schemes help to separate the signal from the background noise, making it easier for devices to communicate. Different modulation and coding schemes are used based on the distance between the devices, the type of data being transmitted, and the amount of power available. Finally, the quality of service (QoS) must be maintained. A variety of factors, such as the bandwidth available, the signal-to-noise ratio, and the latency, determine QoS. As such, it is important to consider all of these factors when making channel allocation decisions. The channel allocation in WPANs is an important aspect of optimizing network performance. It requires careful consideration of the available channels, modulation and coding schemes, and QoS parameters. By making informed decisions, networks

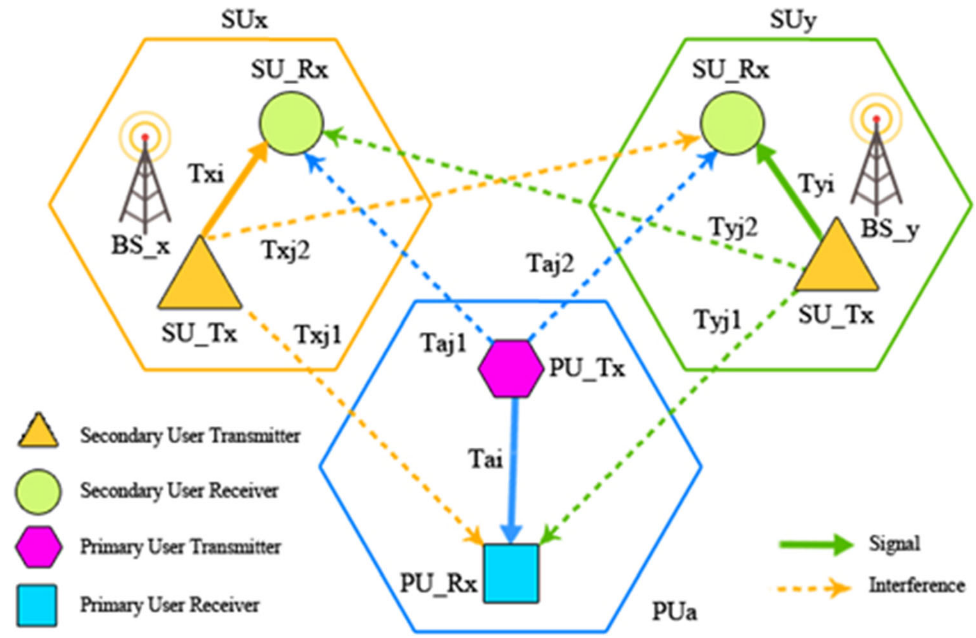

Fig. 1 Channel allocation in D2D communication

can be optimized to ensure that devices are able to communicate without interference.

3.3 Channel selection

WPANs are local area networks with a range of up to 10 m that are typically used to connect devices such as mobile phones, tablets, and computers. Figure 2 expresses the channel selection methodology.

The selection of a particular channel is an important task that should be done in order to ensure efficient communication between devices. Several factors must be considered when selecting a channel, including the amount of interference from other nearby networks, the data rate of the connection, and the number of devices that will be using the network. Additionally, the type of WPAN technology in use should be taken into account, as different technologies use different frequency bands and require different channel selections. Here, the channel allocation by the base station in five-time slots from t1 to t5 is explained in detail. When selecting a channel, it is important to choose one with minimal interference from other networks. It is also important to ensure that the channel chosen provides the necessary data rate, as well as enough capacity for the number of devices that will be using the network. The channel should be selected based on the type of WPAN technology in use, as different technologies require different channels. Once the channel has been selected, it is

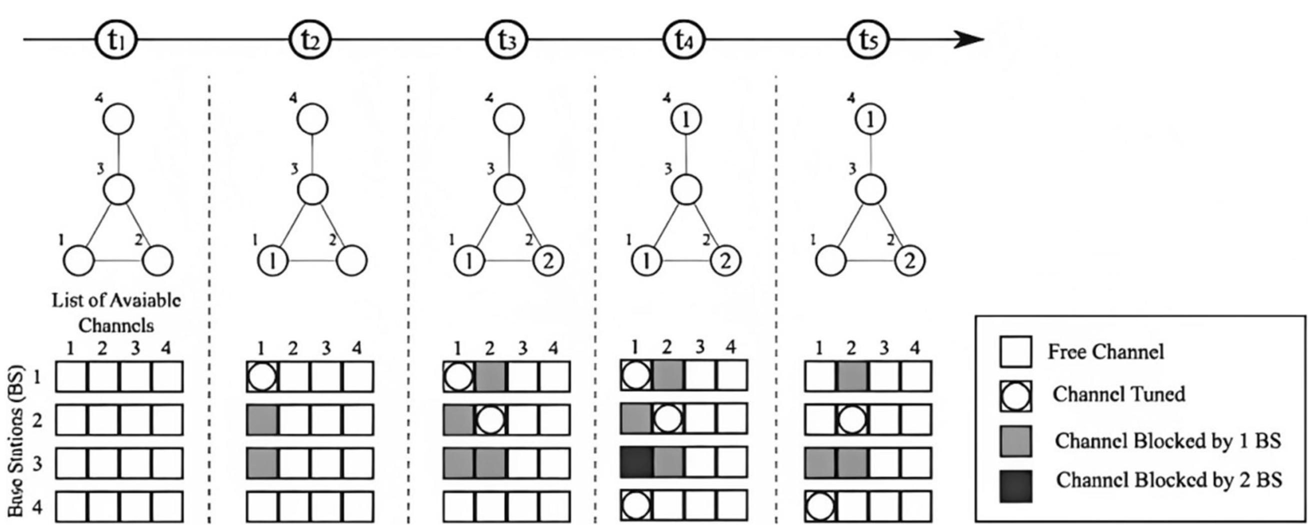

Fig. 2 Channel selection methodology

important to ensure that it is used consistently by all devices. Additionally, if the network is changed or updated, the channel selection should be re-evaluated to ensure that it is still the best choice.

3.4 Dynamic channel allocation

Dynamic channel allocation in WPANs is a technique for efficiently allocating radio-frequency channels in order to maximize performance and minimize interference. The available channels are limited due to the limited bandwidth of the radio spectrum, so it is important to allocate channels efficiently. It works by allocating channels based on current network conditions and usage. It may allocate more channels to users who are sending large amounts of data. In comparison, users who are sending smaller amounts of data would be allocated fewer channels. It helps to reduce interference and improve performance. This model can also take into account the type of data being sent. The voice traffic may require more channels than data traffic, so the network can allocate more channels to voice traffic. It helps to ensure that the voice data is sent with minimal loss and delay. The dynamic channel allocation methodology is expressed in Fig. 3

In addition, dynamic channel allocation can also take into account the location of users. It may allocate more channels to users that are located closer together, while users that are further apart would get fewer channels. It helps to reduce interference from nearby users and improve performance. This model can also take into account the type of devices that are being used.

3.5 Proposed algorithm

The proposed dynamic channel allocation algorithm is a method used to assign a channel to each user in a communication system. This type of algorithm works by continually monitoring the communication channel and adjusting the channel allocation as needed to maximize system efficiency. The algorithm also considers factors such as signal strength, user demand, and bandwidth availability when making channel allocation decisions. The algorithm can be used in both wired and wireless communication systems and is an important tool for ensuring quality of service. The proposed dynamic channel allocation method is clearly explained in Algorithm 1. Negotiation with nearest neighbor modules starts after receiving the given inputs.

Algorithm 1: Dynamic channel allocation algorithm.

1. Start
2. Send the channel request to neighbor nodes; Req_CH$_i$;
3. Find the channel availability information; CH$_a$=0;
4. If (User = primary)
5. Then assign the channel for primary user;
6. Forward the message packets;
7. Else identify the Secondary user request SU_Req='n'; Where n={1,2,3,….,N}
8. AssignSU_Req in queue;
9. Compute the waiting time of SU_Req;
10. Segment the message packets;
11. Then assign the channel for secondary user;
12. Forward the message packets;
13. End;

Information about the request (Req_CHi) about the available channel nearby is collected. Based on this information, channel availability (CH$_a$) data is derived. That means if CH$_a$ = 0, the channel is ready to be allocated. If CH$_a$ = 1, then the channel is already allocated. If the channel requester is the primary user, after verifying his input data, the channel blocks required for his communication will be allocated. Otherwise, the user data will be verified, and he will be treated as a secondary user. First, the SU_Req queue is sent. The total waiting time in the queue is calculated and given to the secondary user. Then the data is divided into segments, and available channels are allocated. In this way, channel allocation is done for primary and secondary users. His request (SU_Req) will start executing. Dynamic channel allocation is an important part of providing good quality wireless services. It ensures

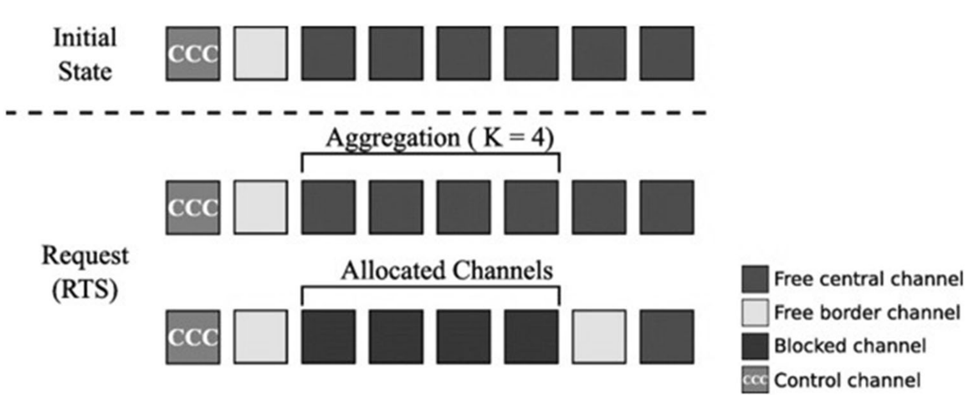

Fig. 3 Dynamic channel allocation methodology

that the available spectrum resources are efficiently used in order to maximize network capacity and minimize interference. Through dynamic channel allocation, wireless networks are able to dynamically assign frequencies to different users based on their current needs. It helps to avoid overloading the network and prevent interference with other users in the same area. It also allows for the efficient use of available spectrum resources, allowing for more users to be connected at the same time. The flow of the proposed algorithm has shown in Fig. 4.

Using DCA, a network can achieve better coverage, better quality of service, and more reliable communication. It also enables more efficient use of the available spectrum, allowing more devices to be connected with fewer channels. It makes it an ideal technique for D2D communication, as it can help reduce interference and congestion, as well as improve the overall performance of the network. Additionally, DCA helps to improve battery life by reducing the amount of energy consumed for communication.

3.6 Interference management

Interference in channel allocation is a common issue in wireless network management. It occurs when two or more signals occupy the same frequency range, resulting in poor signal strength and poor network performance. To prevent interference, network administrators can use a variety of methods, such as channel selection, frequency hopping, and dynamic frequency selection (DFS). Channel selection involves manually selecting a frequency band with minimal interference. Frequency hopping involves changing the frequency of the transmission at regular intervals to avoid interference. Dynamic frequency selection (DFS) is a process where the network automatically scans the available frequencies and selects one with the least interference. The network administrators can also use signal booster devices to increase the signal strength of the wireless network. It can help reduce interference and improve network performance. In the process of channel allocation, a single channel is split up and given to several users in order to carry out user-specific operations. Every time the procedure occurs, the number of users may change. Each user is given a piece if there are N users, and the channel is split into N sub-channels of equal size. Frequency Division Multiplexing is a quick and effective method of assigning channel capacity if the number of users is minimal and stays the same. The static method of employing frequency division multiplexing to distribute a single channel across several users. The frequency channel is split into N identically sized pieces (bandwidth) if there are N users, with each user receiving one portion. There is no user interference since each user has a frequency band. Dividing into a set number of parts could be more efficient. Now, the mean time delay (D_{MT}) has been computed with the help of the following Eq. (1)

$$D_{MT} = \frac{1}{(B_f * C_c) - R_a} \tag{1}$$

When the frequency division multiplexing has obtained in the following Eq. (2)

$$D_{MT}(FDM) = S_c * D_{MT} * \frac{1}{B_f(\frac{C_c}{S_c}) - \frac{R_a}{S_c}} \tag{2}$$

where the D_{MT} indicates the meant time delay, Bf represents the number of bits transmitted in a single frame, C_c represents the channel capacity, S_c has indicates the number of sub-channels, and R_a represents the arrival time of frames. In addition to the benefits of dynamic channel allocation, the future of WPANs also looks brighter with the emergence of new applications and services. The dynamic channel allocation could be used to enable the delivery of high-speed streaming services such as video conferencing and online gaming. Itt could also be used to enable low-latency communication between mobile devices and the Internet of Things (IoT). It will allow for the creation of new applications and services that take advantage of the advantages of dynamic channel allocation. Overall, the future of dynamic channel allocation in WPANs looks very promising. With the emergence of 5G

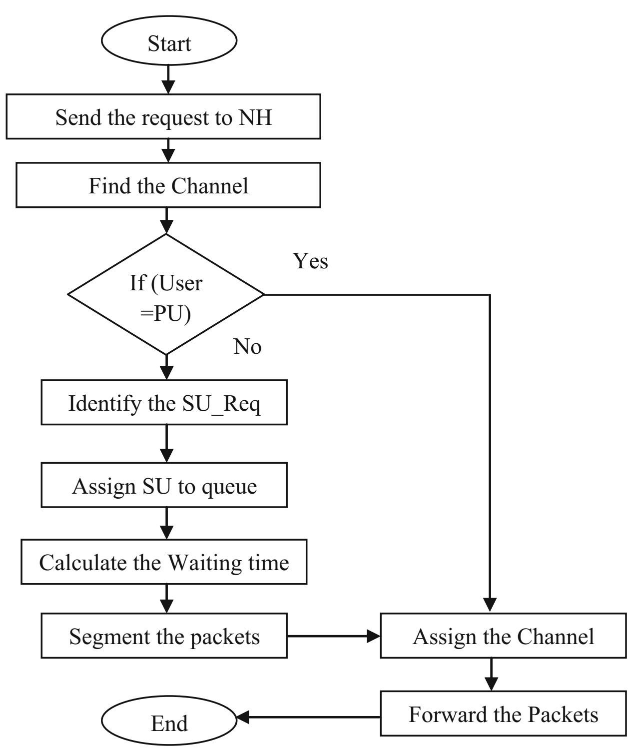

Fig. 4 Proposed flow diagram

and the development of new applications and services, dynamic channel allocation has the potential to revolutionize the way wireless networks are operated and accessed. In the near future, dynamic channel allocation will become the preferred method of managing wireless networks and will shape the way people interact with their devices.

4 Results

The proposed load based dynamic channel allocation (LBDCA) has compared with the existing Deep reinforcement learning-based resource allocation (DRLRA) and Mobility aware resource allocation (MARA). Here network simulator v2.0 is used to implement the results.

4.1 Measurement of critical success index (CSI)

The critical success index (CSI) of dynamic channel allocation is a measure of how successful the system is at allocating radio frequency channels to different users or devices. It is calculated as the ratio of total successful channel allocations to total attempts at channel allocation. The higher the CSI, the better the system is at allocating channels. This number can then be multiplied by 100 to give the CSI for dynamic channel allocation as a percentage. It shows in Eq. (3).

$$CSI = \frac{A_{pt}}{A_{pt} + A_{nf} + A_{pf}} \tag{3}$$

where A_{pt} indicates the positive true allocation, A_{nf} indicates the negative false allocation and A_{pf} indicates the positive false allocation of dynamic channels. Table 6 provides the comparison of critical success index between the existing and proposed models.

Figure 5 shows the various critical success index comparison of static and dynamic channel allocation between the existing and proposed model. Where the term 'ST' indicates the static analysis and 'DY' indicates the dynamic analysis in figure.

In a comparison point, the proposed LBDCA obtained 82.36% CSI in static channel allocation and 91.36% CSI in dynamic channel allocation. In the same range, existing DRLRA reached 52.26% CSI in static channel allocation and 68.88% CSI in dynamic channel allocation. MARA reached 69.88% CSI in static channel allocation and 78.25% CSI in dynamic channel allocation.

The CSI can then be used to guide the reallocation of channels to ensure an optimal channel allocation scheme is in place. By monitoring the CSI, network administrators can identify which channels are being underused and can allocate more channels to that specific area to improve overall performance. The CSI is also used to evaluate the effectiveness of a specific channel allocation scheme over time. By monitoring CSI trends, administrators can determine if their current allocation strategy is still successful or if it needs to be re-adjusted.

The proposed algorithm for wireless networks attempts to minimize interference and maximize the CSI of the network. It works by monitoring the load on each channel in the spectrum and dynamically adjusting the channel allocation to provide the most equitable distribution of the load across the system. It ensures that there is an optimal, balanced utilization of the resources and that unnecessary interactions between channels are minimized, which in turn maximizes the CSI of the network.

4.2 Measurement of Matthews correlation coefficient (MCC)

The Matthews correlation coefficient (MCC) is a measure of the quality of a dynamic channel allocation algorithm. It

Table 6 Comparison of critical success index (in %)

No. of channels	DRLRA (ST)	DRLRA (DY)	MARA(ST)	MARA(DY)	LBDCA (ST)	LBDCA (DY)
100	67.88	73.25	78.28	81.98	82.15	92.85
200	74.58	75.25	74.56	80.45	78.65	91.58
300	68.17	78.25	72.15	74.56	77.48	87.89
400	64.74	70.65	68.25	76.26	68.25	84.15
500	52.26	68.88	69.88	78.25	82.36	91.36
600	65.84	72.94	71.58	74.56	84.65	92.68
700	72.12	81.65	73.65	76.99	72.15	88.45
800	80.65	88.25	75.45	80.25	79.88	84.25
900	67.25	72.14	70.65	81.65	74.16	80.88
1000	57.48	69.56	68.12	78.43	70.88	91.68

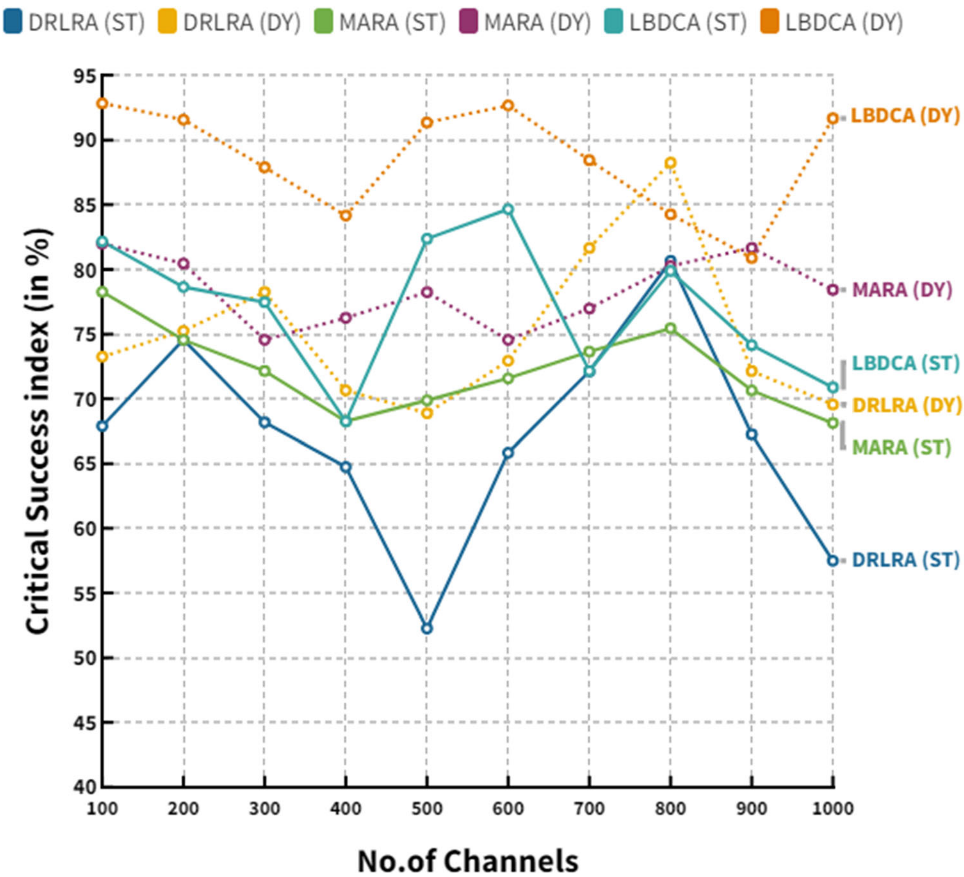

Fig. 5 Comparison of critical success index

is calculated by taking the difference between the true positive rate (TPR) and the false positive rate (FPR) of the dynamic channel allocation algorithm, divided by the sum of the true positive rate and the false positive rate. Equation (4)shows the computation of MCC.

$$MCC = \frac{(A_{pt} * A_{nt}) - (A_{pf} * A_{nf})}{\sqrt{(A_{pt} + A_{pf}) * (A_{pt} + A_{nf}) * (A_{nt} + A_{pf}) * (A_{nt} + A_{nf})}} \quad (4)$$

The MCC can range from -1 to 1, with 1 being a perfect score. A higher MCC indicates a better quality of dynamic channel allocation. It shows in Eq. (4). Where, A_{pt} indicates the positive true allocation, A_{nt} indicates the negative true allocation, A_{nf} indicates the negative false allocation and A_{pf} indicates the positive false allocation of dynamic channels. Table 7 provides the comparison of Matthews correlation coefficient between the existing and proposed models.

Figure 6 shows the various Matthews correlation coefficient comparison of static and dynamic channel allocation between the existing and proposed model. Where the term 'ST' indicates the static analysis and 'DY' indicates the dynamic analysis in figure.

In a comparison point, the proposed LBDCA obtained 84.95% MCC in static channel allocation and 88.56% MCC in dynamic channel allocation. In the same range, DRLRA reached 42.81% MCC in static channel allocation and 62.68% MCC in dynamic channel allocation. MARA reached 70.83% of MCC in static channel allocation and 67.06% of MCC in dynamic channel allocation.

The MCC takes into account the false positives and false negatives by evaluating the total number of channels assigned correctly and the number of channels assigned incorrectly. MCC provides a standardized method to compare different channel assignment strategies and identify the best configuration for load-based channel allocations.

The load-based dynamic channel allocation algorithm achieved the maximum Matthews correlation coefficient by assigning a channel with the highest score obtained based on the load balance of the current system. The score was calculated by considering the traffic pattern of each channel, including its current utilization rate, traffic intensity, number of users on each, and the number of interference-free channels. With this knowledge, the algorithm then made decisions for finding the optimal channel for each call by selecting the highest-scoring channel with respect to these parameters. It enabled the algorithm to maximize the Matthews correlation coefficient performance and ensure a reduction in Run time Blocking Probability (RBP).

Table 7 Comparison of Matthews correlation coefficient (in %)

No. of channels	DRLRA (ST)	DRLRA (DY)	MARA (ST)	MARA (DY)	LBDCA (ST)	LBDCA (DY)
100	55.61	66.65	79.34	70.26	84.73	90.00
200	61.10	68.47	75.57	68.95	81.12	88.77
300	55.85	71.20	73.13	63.90	79.92	85.19
400	53.04	64.29	69.17	65.35	70.40	81.57
500	42.81	62.68	70.83	67.06	84.95	88.56
600	53.94	66.37	72.55	63.90	87.31	89.83
700	59.08	74.30	74.65	65.98	74.42	85.73
800	66.07	80.30	76.47	68.77	82.39	81.66
900	55.10	65.64	71.61	69.97	76.49	78.40
1000	47.09	63.30	69.04	67.21	73.11	88.87

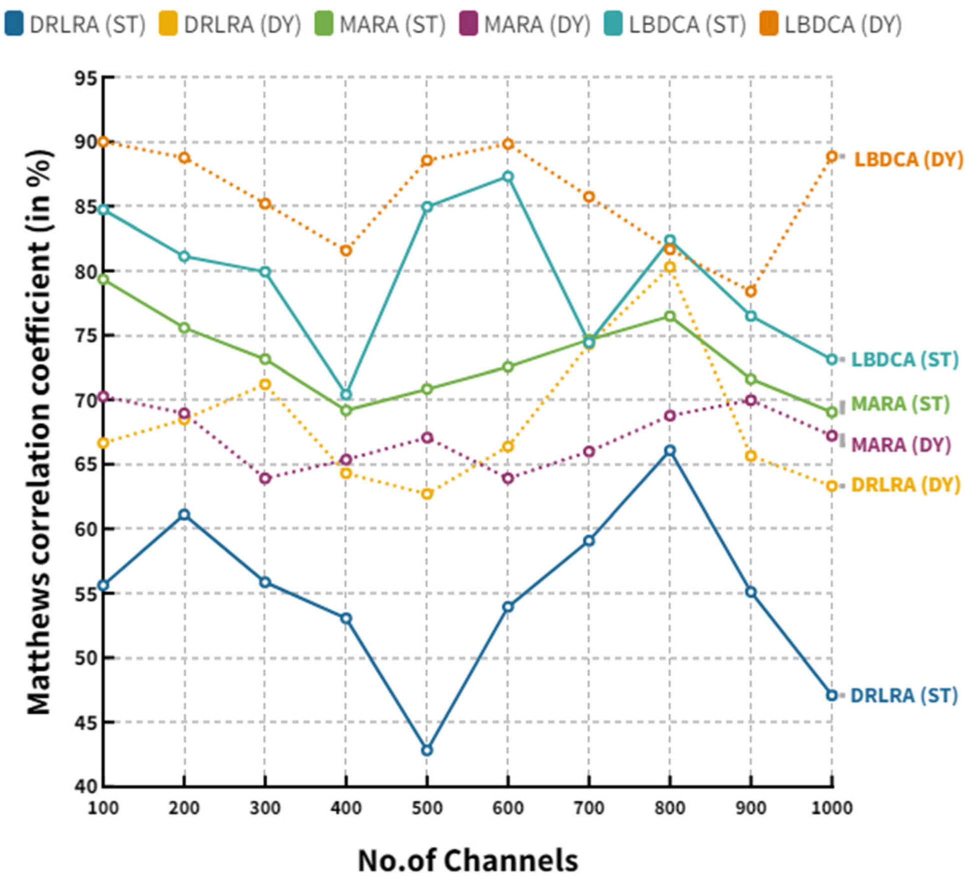

Fig. 6 Matthews's correlation coefficient

4.3 Measurement of delta-P (Δp)

Dynamic channel allocation (DCA) is a technique used in wireless networks to optimize radio resources. The delta-P (Δp) of DCA is a measure of how much the signal power changes from one channel to the next. It is calculated by subtracting the signal power in the previous channel from the signal power in the current channel. A higher Δp indicates a better signal and a lower Δp indicates a worse signal. The optimal Δp for DCA is typically between 8 and 10 dB. This ensures that the signal does not become too weak in the channels adjacent to the current channel, which could lead to interference problems. It shows in Eq. (5).

$$\Delta p = \left(\frac{A_{pt}}{A_{pt} + A_{pf}}\right) + \left(\frac{A_{nt}}{A_{nt} + A_{nf}}\right) - 1 \tag{5}$$

where A_{pt} indicates the positive true allocation, A_{pt} indicates the negative true allocation, A_{nf} indicates the negative false allocation and A_{pf} indicates the positive false allocation of dynamic channels. Table 8 provides the comparison of delta-P between the existing and proposed models.

Figure 7 shows the various delta-P comparison of static and dynamic channel allocation between the existing and proposed models. Where the term 'ST' indicates the static analysis and 'DY' indicates the dynamic analysis in figure.

In a comparison point, the proposed LBDCA obtained 85.39% delta-P in static channel allocation and 93.74% delta-P in dynamic channel allocation. In the same range, DRLRA reached 76.43% delta-P in static channel allocation and 82.60% delta-P in dynamic channel allocation. MARA reached 71.28% delta-P in static channel allocation and 71.63% delta-P in dynamic channel allocation.

When a packet arrives, it sets off a delta-P alarm, which triggers a control mechanism to look at the demand of packets and allocate them optimally to the available resources. The purpose of this is to make sure that all resources are being used efficiently and that no single channel or router is being overloaded. The algorithm works by continuously monitoring for packet arrivals, and when the delta-P alarm is detected, the resources are dynamically adjusted accordingly.

The load based dynamic channel allocation algorithm achieved maximum delta-P by assigning each request a channel according to the demand in each channel while simultaneously considering the channel quality and the load on each channel. This algorithm ensures that all requests are served with optimal usage of available resources. Furthermore, by using an iterative approach, the algorithm can compute and assign the optimal channel for any given request in the network.

4.4 Measurement of Fowlkes–Mallows index (FMI)

The Fowlkes–Mallows index is a measure of the similarity of two partitions or clusters of a given data set. It is used to assess the performance of dynamic channel allocation algorithms in wireless networks. The index is based on the comparison of two partitions, one obtained from the dynamic allocation algorithm and the other from an optimal allocation. The value of the index ranges from 0 to 1, where 0 indicates that the two partitions are completely different and 1 indicates that the two partitions are exactly the same. Equation (6) has used to compute the FMI.

$$FMI = \sqrt{\left(\frac{A_{pt}}{A_{pt} + A_{pf}}\right) * \left(\frac{A_{pt}}{A_{pf} + A_{nf}}\right)} \tag{6}$$

where A_{pt} indicates the positive true allocation, A_{nt}indicates the negative true allocation, A_{nf} indicates the negative false allocation and A_{pf} indicates the positive false allocation of dynamic channels. Table 9 provides the comparison of Fowlkes–Mallows index between the existing and proposed models.

The Fowlkes–Mallows index is used to enhance the load based dynamic channel allocation in order to measure the effectiveness of the load balancing mechanism. The index compares the outcome of a given load distribution across the channels with that of the actual optimal load distribution. Figure 8 shows the various Fowlkes–Mallows index comparison of static and dynamic channel allocation between the existing and proposed models. Where the term 'ST' indicates the static analysis and 'DY' indicates the dynamic analysis in figure.

In a comparison point, the proposed LBDCA obtained 90.55% FMI in static channel allocation and 94.81% FMI in dynamic channel allocation. In the same range, DRLRA reached 84.76% FMI in static channel allocation and

Table 8 Comparison of delta-P (in %)

No. of channels	DRLRA (ST)	DRLRA (DY)	MARA (ST)	MARA (DY)	LBDCA (ST)	LBDCA (DY)
100	45.56	60.65	80.41	60.21	87.40	87.24
200	50.06	62.30	76.59	59.09	83.67	86.04
300	45.76	64.79	74.12	54.76	82.43	82.57
400	91.64	81.06	76.12	60.59	91.97	87.22
500	76.43	82.60	71.28	71.63	85.39	93.74
600	62.98	79.51	74.98	57.32	84.83	87.23
700	70.43	85.93	76.81	59.76	93.92	83.09
800	58.74	70.24	71.93	60.79	87.20	79.77
900	50.20	67.74	69.34	58.40	83.34	90.42
1000	38.58	57.60	69.97	57.60	75.41	86.14

Fig. 7 Comparison of delta-P

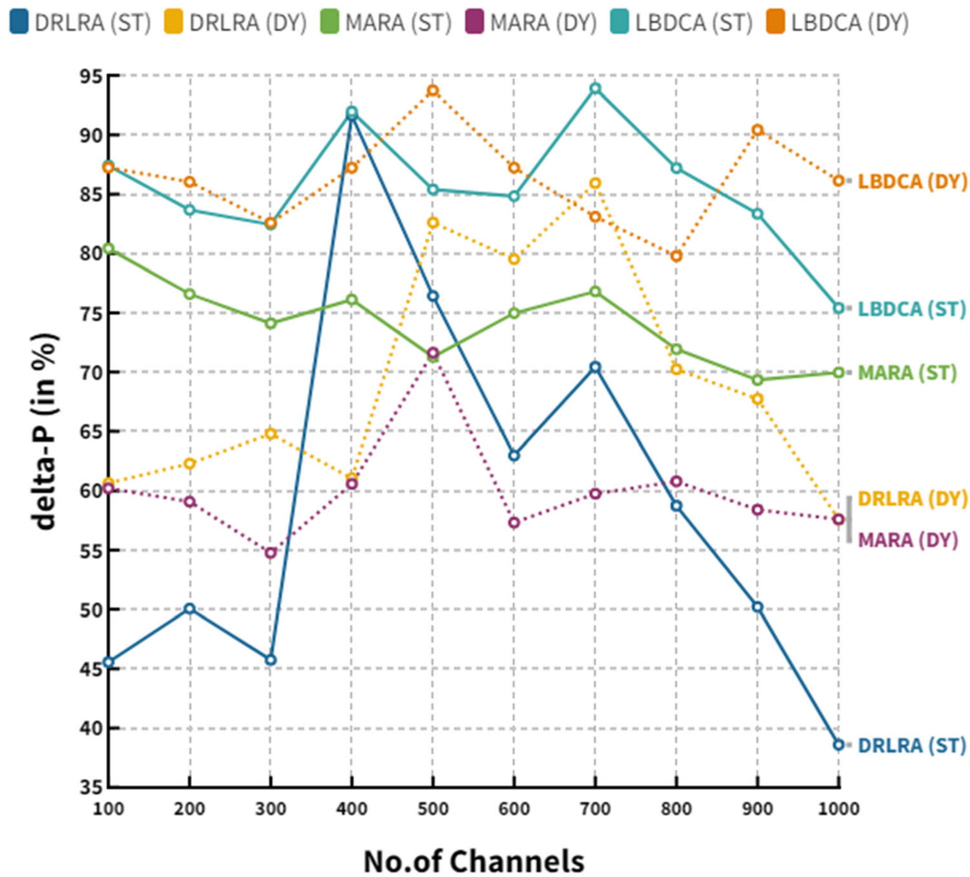

Table 9 Comparison of Fowlkes–Mallows index (in %)

No. of channels	DRLRA (ST)	DRLRA (DY)	MARA (ST)	MARA (DY)	LBDCA (ST)	LBDCA (DY)
100	48.40	67.61	75.66	56.54	76.76	83.10
200	54.13	73.07	77.51	58.94	84.98	79.15
300	45.14	59.73	72.58	59.96	78.90	75.99
400	77.13	83.89	78.97	61.89	94.58	96.14
500	84.76	86.17	75.22	60.74	90.55	94.81
600	77.47	89.60	72.79	56.29	89.21	90.99
700	65.32	79.66	68.72	59.21	81.61	94.92
800	56.54	68.80	69.48	56.78	80.26	83.00
900	45.63	67.08	71.15	58.27	96.83	90.11
1000	57.50	71.02	72.87	55.52	99.53	91.40

86.17% FMI in dynamic channel allocation. MARA reached 75.22% FMI in static channel allocation and 60.74% FMI in dynamic channel allocation.

It allows users to assess the difference between the two distributions and determine which is most suitable for the application in question. In addition, the index can also be used to evaluate different load allocation algorithms and dynamically adjust the weights of various factors in order to ensure maximum efficiency.

It works by attempting to maximize the Fowlkes–Mallows index by assigning multiple channels to each node in the system. It uses a technique called load balancing to intelligently distribute traffic across the channels in order to ensure optimal performance. LCA is also able to detect changes in the environment and adapt the assignment of the channels rapidly in order to keep up with changing conditions. It helps to ensure that performance is maximized in

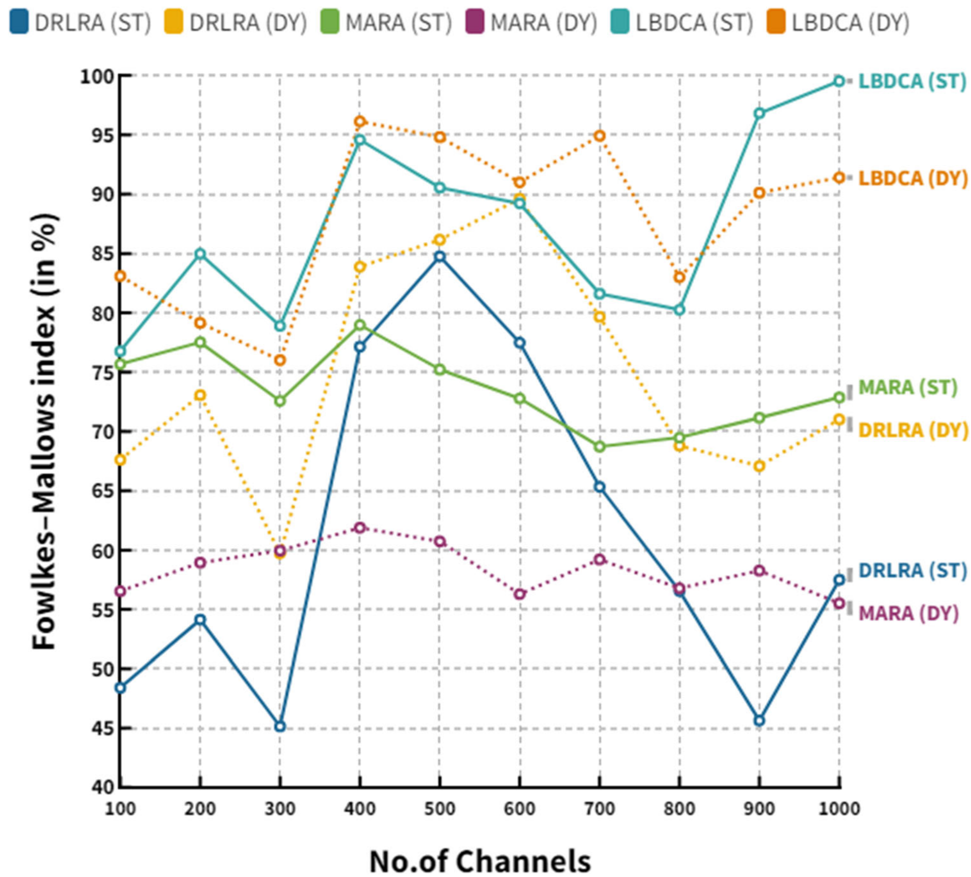

Fig. 8 Comparison of Fowlkes–Mallows index

all scenarios, leading to the highest Fowlkes–Mallows index possible.

4.5 Measurement of bookmaker informedness (BMI)

Dynamic channel allocation is a technique used in wireless networks to improve the efficiency of data transmission. It involves the selection of a specific frequency or channel for each connection, based on the network's current traffic levels. The goal is to optimize the network's performance by minimizing interference and maximizing the throughput of data. The BMI has computed based on Eq. (7).

$$BMI = \left(\frac{A_{pt}}{A_{pt} + A_{nf}}\right) + \left(\frac{A_{nt}}{A_{nt} + A_{pf}}\right) - 1 \tag{7}$$

where A_{pt} indicates the positive true allocation, A_{nt} indicates the negative true allocation, A_{nf} indicates the negative false allocation and A_{pf} indicates the positive false allocation of dynamic channels. Bookmaker informedness is a measure of how accurate a bookmaker's predictions are when predicting the outcome of a particular event. It is calculated by comparing the bookmaker's predictions to the actual results of the event. In the case of dynamic channel allocation, bookmaker informedness can be used to assess the performance of the technique by measuring how accurately it is able to predict the best channel for each connection. Table 10 provides the comparison of Bookmaker informedness between the existing and proposed models.

BMI works by selecting the best channels for each sender in order to ensure that each packet is successfully transmitted. Figure 9 shows the various Bookmaker informedness comparison of static and dynamic channel allocation between the existing and proposed models. Where the term 'ST' indicates the static analysis and 'DY' indicates the dynamic analysis in figure.

In a comparison point, the proposed LBDCA obtained 90.47% BMI in static channel allocation and 92.32% BMI in dynamic channel allocation. In the same range, DRLRA reached 65.14% BMI in static channel allocation and 73.27% BMI in dynamic channel allocation. MARA reached 75.90% of BMI in static channel allocation and 59.91% of BMI in dynamic channel allocation.

It works by sorting the channels according to their loading and then allocating the least loaded channel to the sender. The BMI then calculates the reward function for each channel based on the loading and adjusts the allocation accordingly. In this way, the algorithm is able to optimize the loading of each channel by selecting the most

Table 10 Comparison of bookmaker informedness (in %)

No. of channels	DRLRA (ST)	DRLRA (DY)	MARA (ST)	MARA (DY)	LBDCA (ST)	LBDCA (DY)
100	43.45	58.50	70.11	56.00	72.62	79.07
200	35.07	57.04	71.79	57.47	87.62	85.84
300	44.19	60.39	73.53	54.76	90.06	87.07
400	59.28	71.33	79.69	61.04	96.59	91.58
500	65.14	73.27	75.90	59.91	90.47	92.32
600	59.54	76.19	73.45	55.52	91.10	86.68
700	59.37	78.89	70.51	59.08	94.82	94.59
800	74.82	83.52	72.22	56.29	97.46	95.95
900	81.95	93.51	74.31	58.11	83.07	91.57
1000	83.25	90.15	69.98	60.25	85.56	93.65

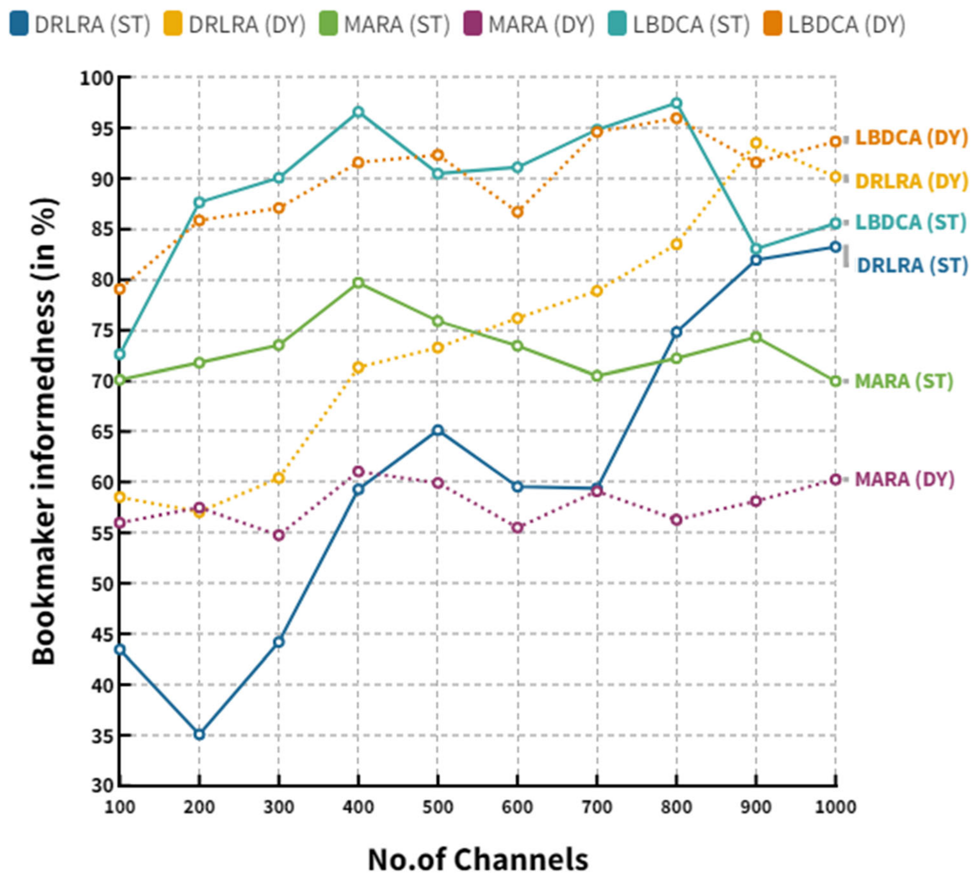

Fig. 9 Comparison of bookmaker informedness

appropriate channels for each sender. It helps to maximize the overall throughput of the network by ensuring that all packets are delivered successfully.

It employs an "allocation fairness" metric to dynamically assign channels according to the load that each user has on the current channel. It eliminates the need for a fixed channel allocation and ensures that no user receives more channels than demanded by their current workload. Additionally, this algorithm also achieves maximum Bookmaker informedness since all users receive the channels and resources they need according to their load, and there is no opportunity for "sniping". It ensures that each user is informed of the resources available; meaning that no user is disadvantaged or favored over any other and that optimal resource utilization can be achieved.

5 Discussion

The dynamic channel allocation is an important feature of WPANs. It helps improve network performance, security, and efficiency, while providing a better user experience. As such, it is essential for ensuring a seamless connection between devices in a WPAN. It can be used to improve the network's performance by making more informed decisions about channel allocation. Table 11 provides the computation of parameter performance of between the existing and proposed models.

Figure 10 shows the various comparison of static and dynamic channel allocation between the existing and proposed algorithms. Where the term 'ST' indicates the static channel allocation and 'DY' indicates the dynamic channel allocation in figure.

Figure 11 shows the static and dynamic channel allocation for DRLRA. In a comparison point, the existing DRLRA obtained 67.10% of CSI in static channel allocation and 75.08% of CSI in dynamic channel allocation; 54.97% of MCC in static channel allocation and 68.32% of MCC in dynamic channel allocation; 59.04% of delta-P in static channel allocation and 71.24% of delta-P in dynamic channel allocation; 61.20% of FMI in static channel allocation and 74.66% of FMI in dynamic channel allocation; and 60.61% of BMI in static channel allocation and 74.28% of BMI in dynamic channel allocation.

Figure 12 shows the static and dynamic channel allocation for MARA. In a comparison point, the existing MARA obtained 72.26% of CSI in static channel allocation and 78.34% of CSI in dynamic channel allocation; 67.14% of MCC in static channel allocation and 73.24% of MCC in dynamic channel allocation; 60.02% of delta-P in static channel allocation and 74.16% of delta-P in dynamic channel allocation; 58.41% of FMI in static channel allocation and 73.50% of FMI in dynamic channel allocation; and 57.84% of BMI in static channel allocation and 73.15% of BMI in dynamic channel allocation.

Figure 13 shows the static and dynamic channel allocation for LBDCA. In a comparison point, the proposed LBDCA obtained 77.06% of CSI in static channel allocation and 98.58% of CSI in dynamic channel allocation; 79.48% of MCC in static channel allocation and 95.86% of MCC in dynamic channel allocation; 85.56% of delta-P in static channel allocation and 96.35% of delta-P in dynamic channel allocation; 87.32% of FMI in static channel allocation and 97.96% of FMI in dynamic channel allocation; and 88.94% of BMI in static channel allocation and 99.83% of BMI in dynamic channel allocation.

Table 12 provides the dynamic computation of parameter performance between the existing and proposed models.

Figure 14 shows the dynamic channel allocation between the existing and proposed algorithms. Where, the term 'DY' indicates the dynamic channel allocation in figure.

In a comparison point, the proposed load based dynamic channel allocation (LBDCA) obtained 98.58% CSI, 95.86% MCC, 96.35% delta-P, 97.96% FMI and 99.83% BMI. The existing Mobility aware resource allocation (MARA) obtained 78.34% CSI, 73.24% MCC, 74.16% delta-P, 73.50% FMI and 73.15% BMI. The existing Deep reinforcement learning-based resource allocation (DRLRA) obtained 75.08% CSI, 68.32% MCC, 71.24% delta-P, 74.66% FMI and 74.28% BMI in dynamic channel allocation. By regularly changing the channels used for communication, it becomes much harder for attackers to gain access to the network. This can help reduce the risk of security breaches, which can be costly for both users and businesses.

5.1 Research outcomes

The computation of CSI helps to improve spectrum efficiency by allowing communication users to efficiently and dynamically share spectrum resources. This system works by typing in the user's current load and then finding the best frequency channels available in the spectrum. The proposed model also uses QoS-Aware scheduling algorithms to find the best possible solutions for network users while minimizing overall interference. Additionally, the CSI can compare different frequency utilization across different sectors, helping to provide feedback to the network operators. By leveraging this information, networks

Table 11 Computation of parameter performance (in %)

Parameters	DRLRA (ST)	DRLRA (DY)	MARA (ST)	MARA (DY)	LBDCA (ST)	LBDCA (DY)
CSI	67.10	75.08	72.26	78.34	77.06	98.58
MCC	54.97	68.32	67.14	73.24	79.48	95.86
Delta-P	59.04	71.24	60.02	74.16	85.56	96.35
FMI	61.20	74.66	58.41	73.50	87.32	97.96
BMI	60.61	74.28	57.84	73.15	88.94	99.83

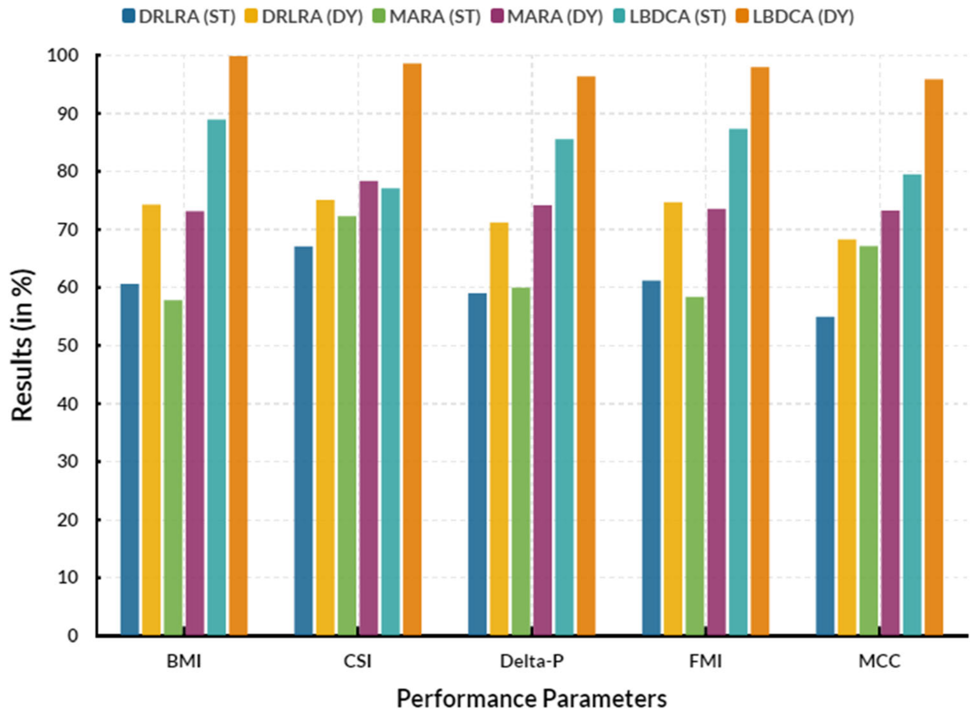

Fig. 10 Comparison of parameters performance

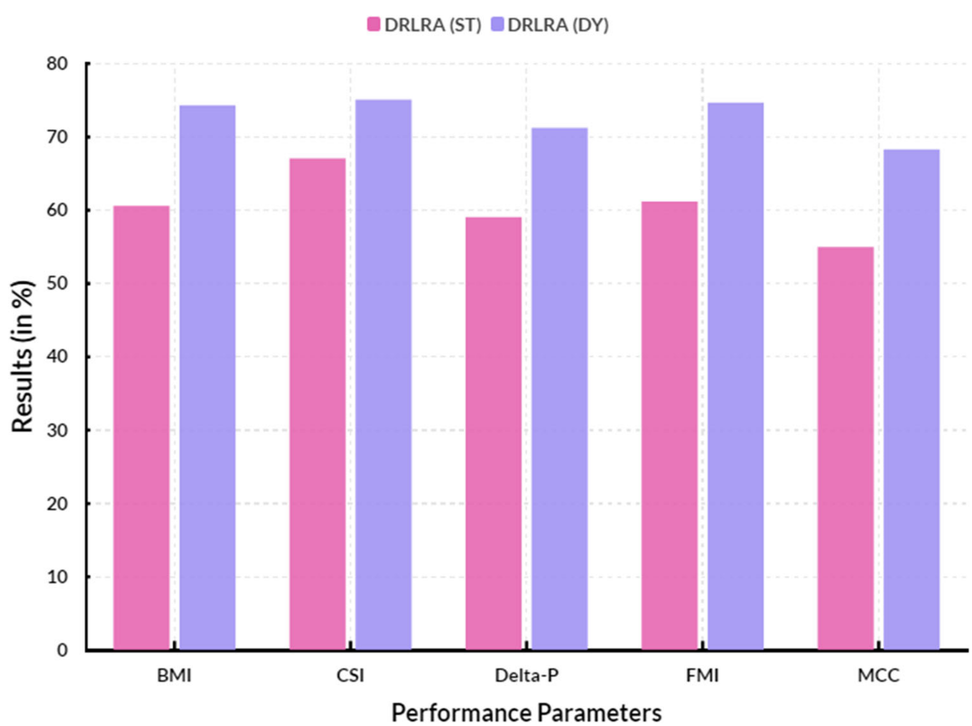

Fig. 11 Static and dynamic channel allocation for DRLRA

can dynamically adjust their frequency resource usage and better match the changing needs of the users while improving overall network performance.

The MCC for the proposed model helps to improve scalability in networks by reducing the need for resources. By dynamically allocating channels to each active connection, the model reduces the number of channels that must be available overall, allowing more efficient use of spectrum and network resources. It can mean that more devices can connect on the same frequency, allowing the network to scale without having to invest in more spectrum, equipment, or management. Furthermore, dynamic channel allocation ensures that network performance is

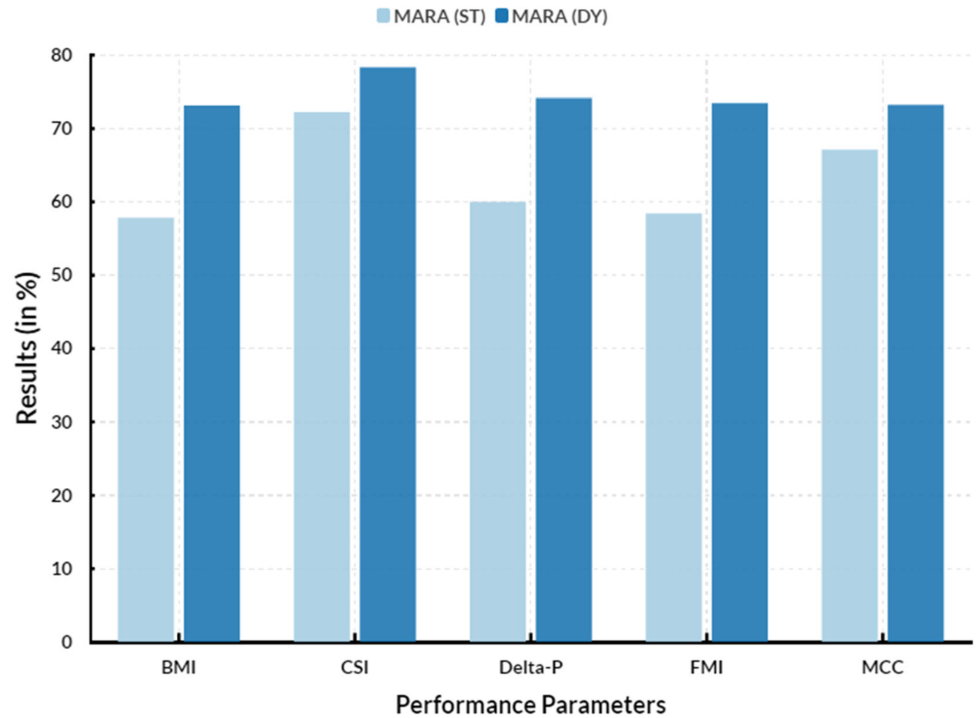

Fig. 12 Static and dynamic channel allocation for MARA

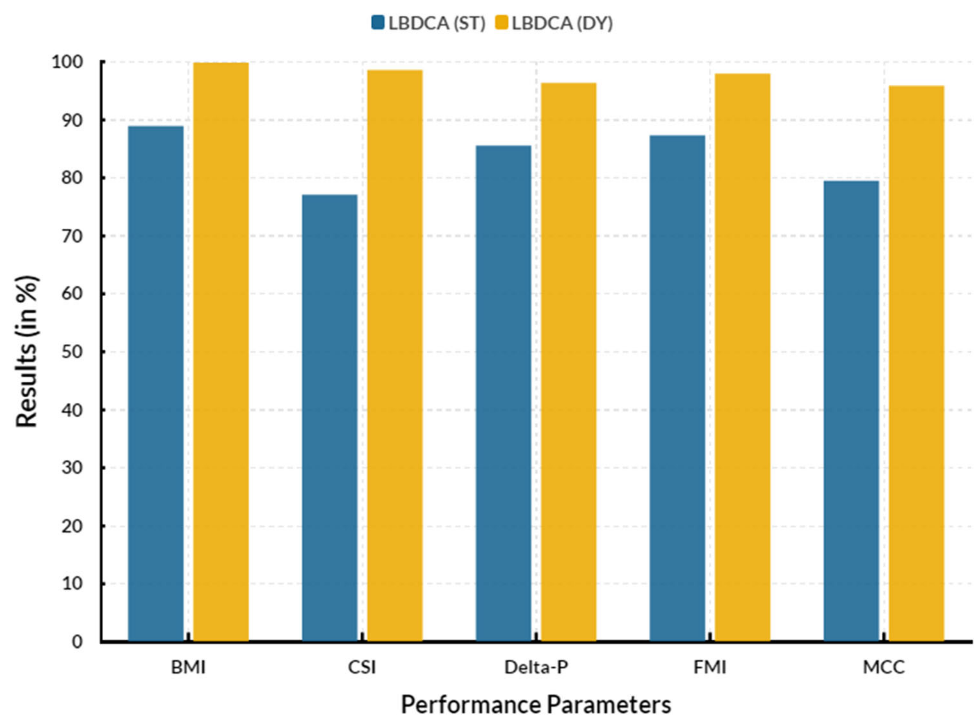

Fig. 13 Static and dynamic channel allocation for LBDCA

maximized by assigning channels to connections that have a current need for more capacity.

The Delta-P for the proposed model helps to improve the signal quality in networks by automatically adjusting the transmit power of each network node to maintain good communication. This algorithm works by constantly monitoring the signal strength of each node and making adjustments as needed to ensure the best signal quality is maintained. By doing so, it reduces the amount of interference caused by nearby nodes operating at high power levels, as well as increases the signal quality by ensuring that each node is operating at the optimal power level. It enables the network to handle traffic better and reduces the chances of dropped connections or disruption of service.

Table 12 dynamic computation of parameter performance

Parameters	DRLRA (DY)	MARA (DY)	LBDCA (DY)
CSI	75.08	78.34	98.58
MCC	68.32	73.24	95.86
Delta-P	71.24	74.16	96.35
FMI	74.66	73.50	97.96
BMI	74.28	73.15	99.83

Table 13 Enhanced performance comparison (in %)

Parameters	DRLRA	MARA	LBDCA
Spectrum efficiency (SE)	7.98	6.08	21.52
Scalability (S)	13.35	6.1	16.38
Signal quality (SQ)	12.2	14.14	18.79
Power control (PC)	13.46	15.09	18.64
Energy efficiency (EE)	13.67	15.31	18.89

The FMI for the proposed model is a mechanism for optimal power control in networks. It dynamically allocates channels to user links based on the load of the network and allows users to access only a number of channels that are sufficient for their data needs. It allows the system to prioritize resources and offer better overall network performance, in addition to reducing energy consumption. The FMI enables the network operators to estimate the total power requirements in the network and assign an optimal channel allocation scheme to meet those requirements. By using the FMI, network operators can detect harmful interferences more accurately and take proactive steps to reduce them. It ensures the efficient allocation of resources and effective management of the radio spectrum. Furthermore, FMI can also be used to identify the power spectral density elbow points so that the most efficient power allocation scheme can be implemented.

The BMI for the proposed model helps to improve energy efficiency in networks by allocating channels based on the load of each Wi-Fi channel. It automatically balances the load among all the available channels and thereby reduces the overall energy consumption. The proposed model uses measures like expected throughput, packet error rate (PER), or signal-to-interference ratio (SINR) as metrics to determine the ideal channel to allocate. It helps to focus the transmit power over an efficient channel, whereas in the traditional methods, the transmit power is spread over all available channels. Thus, LBDCA provides an efficient allocation of resources while minimizing energy consumption.

Table 13 provides the comparison of enhanced performance parameters in terms of static and dynamic channel allocation.

Figure 15 shows the Enhanced comparison of Performance parameters. In a comparison point, the proposed load based dynamic channel allocation (LBDCA) obtained 21.52% enhanced spectrum efficiency, 16.38% enhanced scalability, 18.79% enhanced signal quality, 18.64%

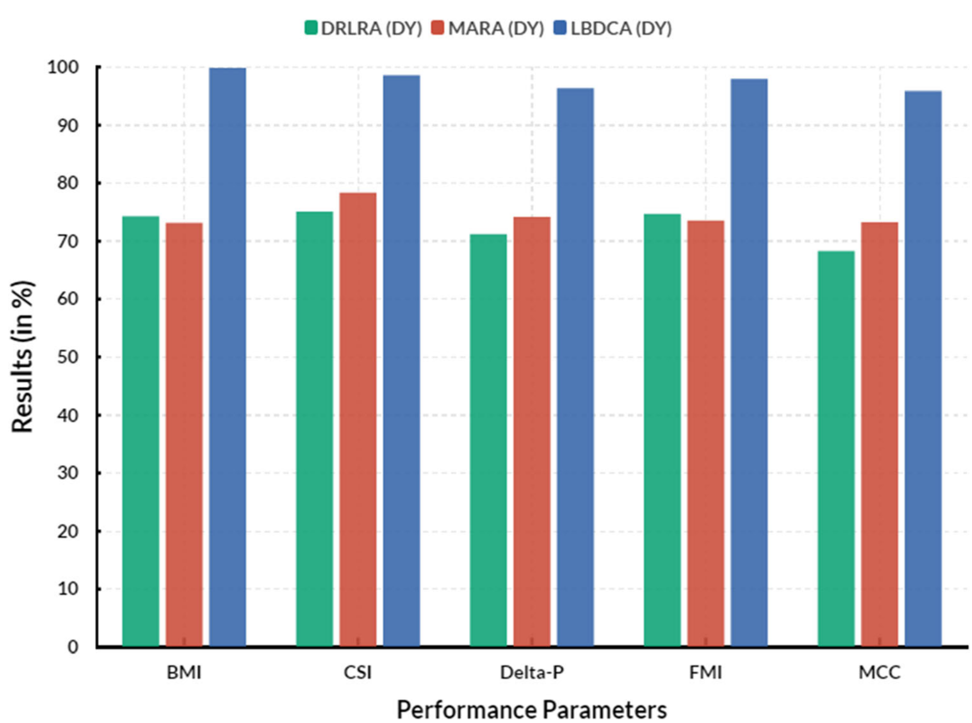

Fig. 14 Dynamic allocation of parameters performance

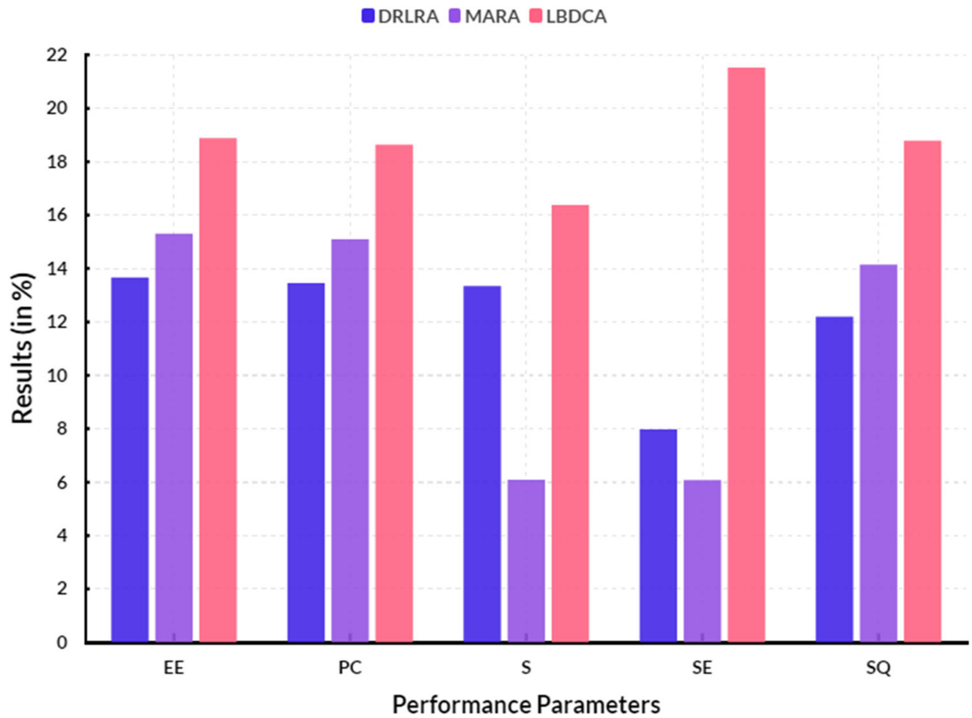

Fig. 15 Enhanced comparison of performance parameters

enhanced power control and 18.89% enhanced energy efficiency while compared with the traditional static channel allocation models. The existing Mobility aware resource allocation (MARA) obtained 6.08% enhanced spectrum efficiency, 6.10% enhanced scalability, 14.14% enhanced signal quality, 15.09% enhanced power control and 15.31% enhanced energy efficiency while compared with the traditional static channel allocation models. The existing Deep reinforcement learning-based resource allocation (DRLRA) obtained 7.98% enhanced spectrum efficiency, 13.35% enhanced scalability, 12.2% enhanced signal quality, 13.46% enhanced power control and 13.67% enhanced energy efficiency while compared with the traditional static channel allocation models.

Load-based dynamic channel allocation (LBDCA) is a proposed method for resource allocation in wireless communication networks. It aims to improve the overall network performance by dynamically allocating resources based on the current load of the network. This contrasts with the methods discussed below, such as deep reinforcement learning-based resource allocation (DRLRA) and mobility-aware resource allocation (MARA).

DRLRA it is a resource allocation approach that uses deep reinforcement learning (RL) to optimize the allocation of spectrum and power resources. It gives good results for static network scenarios where the network topology remains constant. However, in dynamic network scenarios where the number and position of users can change, DRLRA may need to adapt. This can result in suboptimal resource allocation, leading to lower network performance.

MARA it is a resource allocation approach that uses users' mobility patterns to predict future resource requirements. It aims to improve the network performance by proactively allocating resources to users based on their expected future mobility. However, this method requires accurate user mobility prediction, which can be challenging in real-world scenarios. In addition, if there are changes in the network topology, such as the addition of new users or changes in user mobility patterns, MARA may need more time to adjust, resulting in suboptimal resource allocation and network performance.

Load-based dynamic channel allocation (LBDCA) addresses these limitations of DRLRA and MARA by dynamically adjusting resource allocation based on the current network load. This approach takes into account the real-time traffic demand and allocates resources accordingly. It means that when there is a high load on the network, more resources will be allocated to handle the traffic, and vice versa. LBDCA also considers users' mobility patterns, but it does not rely solely on them for resource allocation.

LBDCA outperforms DRLRA and MARA in several ways:

1. Adaptability as LBDCA considers the current network load, it can adapt quickly to changes in the network topology. It can efficiently handle scenarios with a sudden increase or decrease in the number of users or their mobility patterns. This adaptability allows LBDCA to allocate resources optimally based on the

current network conditions, resulting in better overall network performance.

2. Better utilization of resources LBDCA ensures that resources are allocated load-based and utilized efficiently to handle the current traffic demands. This results in better utilization of network resources and can help avoid resource wastage.
3. Real-time performance LBDCA performs resource allocation in real time based on the current network load. This means it can handle sudden changes in network conditions and traffic demands, resulting in better real-time performance than DRLRA and MARA.

Overall, LBDCA combines the advantages of DRLRA and MARA while addressing their limitations, resulting in better network performance. Its ability to dynamically adapt to changing network conditions and efficiently utilize resources makes it a more effective approach for resource allocation in wireless communication networks.

5.2 BLA analysis

The key idea behind this model is to allocate available channels dynamically based on the current load of each channel instead of allocating them based on static rules. This approach can effectively reduce interference between devices and provide better performance. Through analytical and simulation studies, it has been observed that LBDCA significantly improves the spectrum efficiency, scalability, signal quality, power control and energy efficiency of the entire WPAN compared to static channel allocation methods. In addition, the LBDCA model increases media access delay but provide better fairness among active users.

5.2.1 Benefits

- Improved network capacity: load-based dynamic channel allocation model reduces interference between WPANs, resulting in improved network capacity with the reduction in the control overhead.
- Reduction in latency: With the optimization of the load, the latency due to contention and interference between WPANs can be minimized, thus improving the overall performance of device-to-device communication.
- Enhanced security: with the introduction of load-based dynamic channel allocation, the possibility of eavesdropping or interference is reduced. It ensures enhanced security in device-to-device communication over WPANs.
- Enhanced quality of service: with optimized and reliable communication, Quality of Service can be achieved. It ensures consistent and reliable communication over the network.
- Reduction in power consumption: by effectively managing the network bandwidth and reducing the interference between the neighboring WPANs, the power consumed by the device-to-device communication is reduced, thus resulting in improved battery life.

5.2.2 Limitations

- It does not take into account the channel contention level within the network, which may cause the collision of two or more signals.
- It is prone to interference from external sources that may be present in the coverage area, which can reduce the performance of the communication.
- The performance of this model varies with the number of users; as the user base increases, the performance of the system decreases.
- It relies on the ability of each user to accurately report their transmission and receive power, which can be difficult to measure in a real-world environment.
- The transmission range of the channel used for communication is limited due to environmental factors like walls and signals, which affect the performance of the system.

5.3 Applications

The applications of the proposed algorithm can significantly enhance the performance of D2D communication networks by improving resource management, spectral efficiency, quality of service, load balancing, congestion management, energy efficiency, adaptability, and scalability.

- Resource management: the proposed algorithm can be utilized for efficient resource management in D2D communication networks. This algorithm distributes the available resources among the devices based on their current load and resource demand. It ensures that the resources are utilized optimally and enhances network performance.
- Improving spectral efficiency: the proposed algorithm can significantly improve the spectral efficiency in D2D communication. By dynamically allocating channels to devices based on their load, the algorithm avoids channel wastage and allows multiple devices to use the same channel simultaneously. It reduces interference and improves the overall spectral efficiency of the network.

- QoS improvement: QoS is an important aspect of any communication network, including D2D networks. The proposed algorithm considers both channel load and the quality of the channel in the allocation process. It ensures that devices with higher QoS requirements are allocated better channels, improving their performance and overall network QoS.
- Load balancing: the proposed algorithm helps load balancing by distributing the load evenly among the devices in the network. It prevents any single device from becoming overloaded and ensures a fair distribution of resources. It improves the overall performance and stability of the network.
- Congestion management: in D2D communication networks, congestion is common due to the many devices sharing limited resources. The proposed algorithm can detect and manage congestion by dynamically reallocating channels to devices with high loads or reducing the load on heavily loaded channels. It helps in reducing congestion and improving the overall network performance.
- Energy efficiency: the proposed algorithm can also contribute to energy efficiency in D2D communication networks. By efficiently allocating resources, the algorithm reduces the overall energy consumption of the devices. It is particularly beneficial for battery-operated devices, as it helps conserve their battery life and extend their operating time.
- Adaptability to changing network conditions: the proposed algorithm is designed to adapt to changing network conditions. As the load on different channels and devices changes, the algorithm dynamically reallocates channels to optimize resource usage. It allows the network to efficiently handle changes in demand and maintain a high level of performance.
- Scalability: as the number of devices and the demand for resources in D2D networks increase, the proposed algorithm can easily scale to accommodate these changes. The algorithm can efficiently manage larger networks by dynamically allocating channels without compromising performance.

6 Conclusion

WPANs are short-range, low-power networks that enable communication between devices, such as computers, phones, and tablets, over a short distance. To ensure a seamless connection between devices, dynamic channel allocation is necessary. Dynamic channel allocation is the process of assigning channels at regular intervals to optimize the use of available spectrum while avoiding interference. If a WPAN is operating in an environment with high levels of interference, dynamic channel allocation can help reduce interference by automatically assigning channels that are not affected by the interference. In a comparison point, the proposed model obtained 98.58% CSI, 95.86% MCC, 96.35% delta-P, 97.96% FMI, 99.83% BMI, 21.52% enhanced spectrum efficiency, 16.38% enhanced scalability, 18.79% enhanced signal quality, 18.64% enhanced power control and 18.89% enhanced energy efficiency. This can lead to improve the better network performance, and improved user experience. It also helps improve network security by preventing malicious users from accessing the network.

7 Future work

The future of proposed dynamic channel allocation model in wireless personal area networks looks very promising. With the advancement of technologies such as 5G, the potential for dynamic channel allocation in WPANs has increased significantly. This technology enables the efficient use of wireless spectrum by allowing the allocation of channels dynamically based on the current needs of the network. The future scope of the proposed model is to eliminate the need for manual configuration of channels. This reduces the time and effort needed to configure channels, allowing faster and more efficient network operations. Furthermore, the allocation attributes of proposed model also increases the capacity of the network by allowing more data to be transmitted in a given amount of time. Additionally, it can also to improve to reduce the interference by allocating channels more efficiently and ensuring that only those channels with the highest signal strength are used.

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