electronics

MDPI

Article

Smart Load-Based Resource Optimization Model to Enhance the Performance of Device-to-Device Communication in 5G-WPAN

Jaganathan Logeshwaran [1], Thangavel Kiruthiga [2], Raju Kannadasan [3,*], Loganathan Vijayaraja [4], Ali Alqahtani [5], Nayef Alqahtani [6] and Abdulaziz A. Alsulami [7]

[1] Department of Electronics and Communication Engineering, Sri Eshwar College of Engineering, Coimbatore 641202, India
[2] Department of Electronics and Communication Engineering, Vetri Vinayaha College of Engineering and Technology, Thottiam 621214, India
[3] Department of Electrical and Electronics Engineering, Sri Venkateswara College of Engineering, Sriperumbudur 602117, India
[4] Department of Electrical and Electronics Engineering, Sri Sairam Institute of Technology, Chennai 600044, India
[5] Department of Networks and Communications Engineering, College of Computer Science and Information Systems, Najran University, Najran 61441, Saudi Arabia
[6] Department of Agricultural systems Engineering, College of Agricultural and Food Sciences, King Faisal University, Al-Hofuf 31982, Saudi Arabia
[7] Department of Information Systems, Faculty of Computing and Information Technology, King Abdulazz University, Jeddah 21589, Saudi Arabia
* Correspondence: kannadasanr@svce.ac.in

Abstract: In wireless personal area networks (WPANs), devices can communicate with each other without relying on a central router or access point. They can improve performance and efficiency by allowing devices to share resources directly; however, managing resource allocation and optimizing communication between devices can be challenging. This paper proposes an intelligent load-based resource optimization model to enhance the performance of device-to-device communication in 5G-WPAN. Intelligent load-based resource optimization in device-to-device communication is a strategy used to maximize the efficiency and effectiveness of resource usage in device-to-device (D2D) communications. This optimization strategy is based on optimizing the network's resource load by managing resource utilization and ensuring that the network is not overloaded. It is achieved by monitoring the current load on the network and then adjusting the usage of resources, such as bandwidth and power, to optimize the overall performance. This type of optimization is essential in D2D communication since it can help reduce costs and improve the system's performance. The proposed model has achieved 86.00% network efficiency, 93.74% throughput, 91.94% reduced latency, and 92.85% scalability.

Keywords: WPAN; access point; efficiency; resource; allocation; communication; energy; load; optimization; device to device; throughput; latency; scalability

check for updates

Citation: Logeshwaran, J.; Kiruthiga, T.; Kannadasan, R.; Vijayaraja, L.; Alqahtani, A.; Alqahtani, N.; Alsulami, A.A. Smart Load-Based Resource Optimization Model to Enhance the Performance of Device-to-Device Communication in 5G-WPAN. *Electronics* **2023**, *12*, 1821. https://doi.org/10.3390/electronics12081821

Academic Editor: Christos J. Bouras

Received: 16 March 2023
Revised: 31 March 2023
Accepted: 6 April 2023
Published: 12 April 2023

Copyright: © 2023 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

1. Introduction

Wireless communication network resources are defined in specific terms, such as their capacity, spectrum, channels, and so on, and they need to be allocated according to the user's requirements. The three main use cases exist together in many real-world scenarios, and they are competing over the same set of timing and frequency resources, which results in natural trade-offs between their performance [1]. Resource allocation plays a substantial role in maintaining a friendlier experience for cellular-based application end users, enterprise partners, and customers. Allocating resources for the Resource Bands (RBs) in some policies would increase the utilization of the allocated RBs on Long-Term Evolution (LTE) networks [2]. An optimum solution for allocating RBs is proposed in this study, which does

not employ the conventional options at the QCI layer, under conditions where total User Equipment (UE) data requirements are lower than the capacity provided by radios. In the group UE, we schedule according to the number of buffered UE data, with a larger number of buffered data giving priority to RB radio resource allocation [3]. If more than one UEs group is present following the adoption of dynamic Quality of Service Class Identifier (QCI) layer procedures, then sequences are allocated according to the group priorities. The basic idea is to efficiently maximize allocated resources within each planning period while satisfying the quality-of-service requirements [4]. The three mechanisms can cooperate, in essence setting up a network architecture that uses predictions to allocate users effectively and manage the available resources. Each layer executes a subset of functions (related to broadcasting and/or receiving) required to communicate between two processes [5]. Each layer communicates with its own counterpart; for example, the network layer on a transmitter communicates with the network layer on a receiver [6]. The data rates and latency were framed as the constraints on users' quality-of-service (QoS) requirements, while the energy efficiency was ultimately improved through joint optimization of the transmission modes, the beam form vectors, and the power and resource allocation blocks [7]. The objective function of the problem can be minimized by optimizing transmission power first for Internet of Things (IoT) users, then optimizing resource block indicators. The regression-based mechanism is successful at anticipating the user's movements through the network, which leads to better resource management and lower power consumption [8]. The least interference resource allocation scheme for a 5G cell phone network using device-to-device (D2D) communication over hopping for purposeful mitigation of interference was raised. The combined energy management and resource allocation under the scenario of a multiplexed single-link, single-channel communication, proposed a resource allocation mechanism based on graph theory for quality-of-service guarantees to both cell users and D2D users [9]. References focus on the resource scenario for multiplexed single-channel resources of multi-users, joint access control, power control, and channel allocation, in order to maximize system capacity, while also guaranteeing quality of service to existing cellular users and D2D users [10].

When more memory management units (MMUs) are present in a system, performance benefits from partial offloading enabled by D2D are clearer, which indicates that the partial offloading models enabled by D2D are appropriate for the user-intensive scenarios. Existing partial offloading is affected by the constraints on communication resources, resulting in high latency [11]. Because helper computing resources are utilized during partial D2D-enabled offloading, latency in such systems can be kept at a low level, where the computing resources at the edge servers are sparse. The pure D2D communications model groups of D2D users intelligently, distribute resources according to the color of vertices, and maximize the system capacity based on ensuring the signal quality of the cell users and edge cell users [12]. In the multiplexed model, there is no frequency use difference between D2D and cellular communications. In the traditional scenario, BS distributes resources between the cellular and D2D users; specialized resource allocations and appropriate power distributions are be applied at D2D units; and interception and reliability are controlled. D2D communications enable user devices (UEs) in proximity to share information via direct communication, which could act as a backbone for an LTE-A network by reusing spectrum resources [13]. In particular, device-to-device (D2D) communications are considered the core technology of 5G wireless systems that can enable services including real-time data sharing and video. Through modeling validation, the proposed algorithm has greatly improved system power efficiency and resource utilization when compared with a scenario in which D2D users could reuse at most one of the Centralized Unit (CU) resources, providing an intelligent optimization solution for the particle swarm to optimize the energy efficiency of systems. Wireless networks are moving toward higher energy efficiency, better resource utilization, and higher capability. The cellular communications resources and computing resources from edge servers are allocated to each multi-user (MU). Optimization for interference and shared resources improves

device-to-device communication performance [7]. A power distribution algorithm based on particle swarm optimization is proposed for the interference resolution between users during D2D communications implementation on cell networks. D2D user pairs are allowed to reuse resources from multiple cellular users, increasing their overall power efficiency according to the quality-of-service constraints, as well as changing location and velocity within particle swarms. According to the references, to improve spectral efficiency and the system capacity, a cellular user allows the sharing of spectrum resources between various D2D pairs.

Bosio, S. et al. [14] discussed an issue in devices that are not properly configured for communication that can lead to an inefficient use of resources. Security concerns can also arise in device-to-device communication, which can impact the optimization of resources. Purandare, R. et al. [15] expressed that a challenge in load-based resource optimization for device-to-device communication is that the devices need to be able to accurately estimate the number of resources that are required for the communication. Lima, M. P. et al. [16] discussed how resource allocation is often difficult to perform because communication often takes place over some time, and the resources required can vary depending on the time of day or the week. In addition, the devices need to be able to take into account the different types of traffic that may be present on the network, as well as the different priorities that may be assigned to different types of traffic. Pawar, R. S. et al. [17] expressed that the biggest challenge for resource optimization in device-to-device communication is the limited resources available on each device. This means that communication between devices must be carefully managed to avoid overuse of resources and potential conflicts. Radha, P. et al. [18] stated that to optimize resources, communication protocols must be designed to be as efficient as possible. This includes minimizing the amount of data that are transferred between devices, as well as using compression techniques to reduce the size of data packets. In addition, communication protocols should be designed to allow devices to share resources, such as using a shared communication channel or power source.

Alani, T. O. et al. [19] expressed that a challenge for resource optimization is the need to support a wide range of devices with different capabilities. This includes devices with different amounts of memory, processing power, and communication bandwidth. As such, it is important to design communication protocols that can be scaled to support a wide range of devices. Liu, R. et al. [20] asserted that it is important to consider the impact of resource optimization on battery life. Although reducing the amount of data transferred between devices can save energy, it may also reduce the quality of the communication. As such, it is important to find a balance between reducing energy consumption and maintaining communication quality. Nayakwadi, N. et al. [21] expressed that the optimal load-based resource allocation for device-to-device communication will vary depending on the specific situation and context; however, some tips for allocating resources in this way include understanding the devices' capabilities and limitations, as well as identifying and prioritizing the most important communication tasks. Additionally, it can be helpful to create a load-based resource allocation plan in advance and then adjust it as needed based on real-time conditions. Xiao, H. et al. [22] stated that the resource optimization issues in device-to-device communication are many and varied. One of the most pressing issues is the efficient use of radio resources. In a device-to-device communication system, radio resources are used to communicate between devices. The efficient use of radio resources is essential to the success of any device-to-device communication system.

Das, S. K. et al. [23] expressed that a pressing issue is the efficient use of battery power. In a device-to-device communication system, battery power is used to communicate between devices. The efficient use of battery power is essential to the success of any device-to-device communication system. Van Truong, T. et al. [24] discussed another pressing issue, which is the efficient use of data. In a device-to-device communication system, data are used to communicate between devices. The efficient use of data is essential to the success of any device-to-device communication system. Liu, J. et al. [25] stated that these resource optimization issues are important in a device-to-device communication

system. All of these resource optimization issues must be addressed for a device-to-device communication system to be successful. Fu, Y. et al. [26] discussed the many benefits to resource optimization in device-to-device communication. One benefit is that it can help reduce the amount of data that are transferred between devices. This can help to save on data usage and bandwidth costs. Aghapour, Z. et al. [27] expressed that the benefit is that it can help to improve communication speeds. By optimizing the resources that are used, it can help to reduce the amount of time that is needed to transfer data between devices. Zhang, L. et al. [28] stated that when two devices can communicate with each other directly, without going through a server or other intermediary, it is called device-to-device communication. One of the advantages of this type of communication is that it can be much more efficient than other methods since there is no need to route data through a third party. This can be especially helpful when dealing with large amounts of data, or when time is of the essence. Zheng, Z. et al. [29] expressed that an advantage of device-to-device communication is that it can be more secure than other methods. When data are passed through an intermediary, there is always the risk that it could be intercepted or that a third party could gain access to it. When devices communicate directly with each other, that risk is eliminated. Bi, X et al [30] asserted that device-to-device communication can be more convenient than other methods since it does not require users to go through a separate app or website. All they need to do is connect their devices and start exchanging data. This can be a big advantage in situations where time is limited, or users are on the go. Haus M. et al. [31] discussed security and privacy in device-to-device (D2D) communication, which protects the data and links between two devices. It includes authentication, authorization, encryption, and other measures to protect the data from unauthorized access, alteration, or duplication. Additionally, privacy measures, such as data anonymization and obfuscation, can be used to protect user data from potential identification and profiling. Asadi, A. et al. [32] discussed how the device-to-device (D2D) communication in cellular networks is a communication technology that allows two mobile devices to directly communicate with one another without going through a base station or other intermediary devices. It is a type of proximity-based communication that allows devices to share data, such as audio, video, and messages, over a short-range radio frequency connection. D2D is expected to improve network performance and reduce congestion while providing users with enhanced services. Waqas, M. et al. [33] discussed mobility-aware D2D communication between two or more devices near each other. This type of communication typically involves devices that are either on the same network or have a direct connection to one another. It is essential for developing new services and applications in the Internet of Things (IoT) and for providing secure, reliable, and efficient communications. The main principles of mobility-aware D2D communications include dynamic resource allocation, efficient routing, and mobility management. Dynamic resource allocation ensures that the available resources are used most efficiently. Table 1 provides a comprehensive analysis of the related works.

From the above comprehensive analysis, the following issues were identified:

- Device-to-device (D2D) communication often has limited bandwidth due to the physical limitations of the devices. This can result in a bottleneck in data transmission and can limit the effectiveness of load-based resource allocation.
- D2D communication is often subject to interference from other devices or networks, which can reduce the quality of the communication and make load-based resource allocation more difficult.
- Security is a major challenge in D2D communication, as the devices must be trusted to use the resources efficiently and securely.
- D2D communication often requires a significant amount of power, as the devices must constantly be in communication with one another. This can make load-based resource allocation difficult, as the devices must be able to balance their power consumption with the number of resources they need.

- Congestion can be a major issue in D2D communication, as the devices are often communicating with one another nearby. This can lead to a significant amount of data being transferred and can make load-based resource allocation difficult.

Table 1. Comprehensive analysis.

Authors	Identified Issues
Bosio, S. et al. [14]	An issue is devices that are not properly configured for communication can lead to inefficient use of resources. Security concerns can also arise in device-to-device communication, which can impact the optimization of resources.
Purandare, R. et al. [15]	A challenge in load-based resource optimization for device-to-device communication is that the devices need to be able to accurately estimate the amount of resources that are required for the communication.
Lima, M. P. et al. [16]	The devices need to be able to take into account the different types of traffic that may be present on the network, as well as the different priorities that may be assigned to different types of traffic.
Pawar, R. S. et al. [17]	The biggest challenge for resource optimization in device-to-device communication is the limited resources available on each device.
Radha, P. et al. [18]	To optimize resources, communication protocols must be designed to be as efficient as possible. This includes minimizing the amount of data that are transferred between devices, as well as using compression techniques to reduce the size of data packets.
Alani, T. O. et al. [19]	A challenge for resource optimization is the need to support a wide range of devices with different capabilities. This includes devices with different amounts of memory, processing power, and communication bandwidth.
Liu, R. et al. [20]	It is important to consider the impact of resource optimization on battery life. Although reducing the amount of data transferred between devices can save energy, it may also reduce the quality of the communication.
Nayakwadi, N. et al. [21]	An optimal load-based resource allocation for device-to-device communication will vary depending on the specific situation and context. It can be helpful to create a load-based resource allocation plan in advance and then adjust it as needed based on real-time conditions.
Xiao, H. et al. [22]	The resource optimization issues in device-to-device communication are many and varied. One of the most pressing issues is the efficient use of radio resources.
Das, S. K. et al. [23]	In a device-to-device communication system, battery power is used to communicate between devices. The efficient use of battery power is essential to the success of any device-to-device communication system.
Van Truong, T. et al. [24]	In a device-to-device communication system, data are used to communicate between devices. The efficient use of data is essential to the success of any device-to-device communication system.
Liu, J. et al. [25]	Resource optimization issues are important in a device-to-device communication system. All of these resource optimization issues must be addressed for a device-to-device communication system to be successful.
Fu, Y. et al. [26]	One benefit is that it can help reduce the amount of data that is transferred between devices. This can help to save on data usage and bandwidth costs.
Aghapour, Z. et al. [27]	The benefit is that it can help to improve communication speeds. By optimizing the resources that are used, it can help to reduce the amount of time that is needed to transfer data between devices.
Zhang, L. et al. [28]	One of the advantages of this type of communication is that it can be much more efficient than other methods since there is no need to route data through a third party. This can be especially helpful when dealing with large amounts of data, or when time is of the essence.
Zheng, Z. et al. [29]	When data are passed through an intermediary, there is always the risk that it could be intercepted or that a third party could gain access to it. When devices communicate directly with each other, that risk is eliminated.
Bi, X. et al. [30]	Device-to-device communication can be more convenient than other methods since it does not require users to go through a separate app or website.

There are several issues to consider when optimizing resources in device-to-device communication. One is the problem of load balancing. This occurs when devices are not evenly matched in terms of their processing or communication capabilities, which can lead to an uneven utilization of resources. The main novelty of this research has provided an optimal solution to the above-mentioned issues. In contrast, efficient routing ensures that

data are sent through the most direct route between two devices. These networks provide dedicated and reliable communications between two or more devices while reducing the power consumption of devices. They are the following:

- Improved resource utilization: Smart load-based resource optimization in device-to-device communication can improve the utilization of resources by efficiently managing the load. It can intelligently allocate resources to the communication devices that require them, thus reducing the wastage of resources.
- Increased network performance: Smart load-based resource optimization in device-to-device communication can improve the performance of networks by minimizing interference between adjacent devices. This helps to reduce packet losses, reduce latency, and improve throughput.
- Reduced energy consumption: Smart load-based resource optimization in device-to-device communication can reduce energy consumption by limiting the amount of energy consumed by each device. This helps to conserve energy, thus reducing the overall energy consumption of the network.
- Improved reliability: Smart load-based resource optimization in device-to-device communication can improve the reliability of the communication by ensuring that the resources are allocated to the right devices. This helps to reduce packet losses and latency, thus improving the reliability of the communication.

The remaining sections of the paper have been organized as follows: Section 2 provides details about the methodology of the research. Section 3 expresses the details and algorithm of the proposed models. Section 4 discusses the analytical information related to the research and Section 5 discusses the comparative analysis between the existing and proposed model. Finally, Section 6 provides details about the conclusion and future enhancements to the proposed model.

2. Methodology

Device-to-device (D2D) communication involves two or more mobile devices communicating directly with each other instead of relying on a central node or base station. To optimize the use of resources in D2D communication, load-based resource optimization can be used. This is a technique that dynamically allocates resources based on the current load on the network. The resource allocation mechanism is expressed in the following Figure 1.

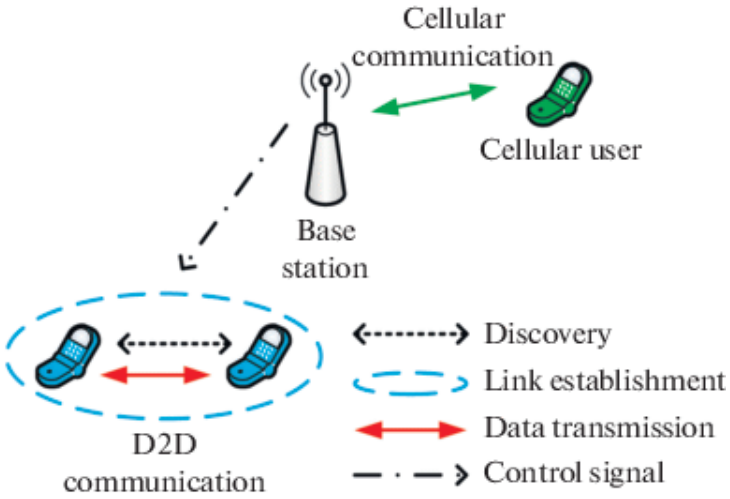


Figure 1. Resource allocation for D2D communications in wireless networks (Green arrow represents the communication channel).

The main goal is to improve the overall system performance by allocating resources more efficiently. To achieve this, the system must continuously monitor the current load on the network and adjust the number of resources allocated to each device accordingly. For example,

if one device is using a large number of resources, the system can reallocate resources to other devices to balance the load. This can help ensure that all devices have enough resources to operate efficiently. Additionally, this technique can also help reduce congestion on the network and ensure that all devices have access to the resources they need.

2.1. Dynamic Bandwidth Allocation

The Dynamic Bandwidth Allocation (DBA) device is a tool that helps to manage communication between devices on a network. It allows for the efficient allocation of bandwidth between devices and can help to improve communication speeds and overall network performance. The DBA device works by constantly monitoring the amount of bandwidth being used by each device on the network. When one device is using more bandwidth than another, the DBA device will automatically adjust the allocation of bandwidth so that both devices have an equal share. This helps to ensure that all devices on the network have the same opportunity to communicate at high speeds.

2.2. Adaptive Resource Allocation

This approach involves allocating resources to the devices based on their current load but also taking into account the future load of the devices. This helps to ensure that the resources are optimally allocated and that the performance of the device-to-device communication is maintained. Assuming you would like a brief overview of adaptive resource allocation in device-to-device communication, device-to-device communication, or D2D for short, is a communication method where devices can communicate directly with each other without having to go through a third party, such as a base station. This can be useful in several different scenarios, for example when two devices are close to each other and there is a high amount of traffic.

2.3. Load Balancing

This approach involves ensuring that the load on each device is evenly distributed. This helps to avoid any single device becoming overloaded and ensures that the performance of the device-to-device communication is maintained. Device-to-device communication is a rapidly growing area of wireless communication. As more and more devices are connected wirelessly, the need for efficient load balancing becomes more important. Load balancing is the process of distributing traffic across a network so that no single device is overloaded. In device-to-device communication, load balancing is essential for ensuring that all devices can communicate effectively. There are many different ways to achieve load balancing.

2.4. Network Coding

This approach involves encoding the data from the different devices to reduce the traffic load on the network. This helps to ensure that the performance of the device-to-device communication is maintained. In device-to-device communication, network coding is used to improve the efficiency of data transmission. By encoding the data before they are sent, the data can be sent more quickly and with less error. This is especially useful in situations where the data are being sent over a long distance or where there is a lot of traffic on the network. Network coding can be used in a variety of different ways to improve the efficiency of data transmission. For example, it can be used to compress the data so that they take up less space on the network. It can also be used to encrypt the data so that they are more secure.

3. Proposed Model

Load-based resource allocation is an important strategy for device-to-device (D2D) communication. Load-based resource allocation enables D2D communication to be more efficient by utilizing resources based on the current load of the network. With load-based resource allocation, the resources are allocated in a dynamic manner, which helps to improve the efficiency of the communication. It can help to reduce the amount of congestion

in the network and provide a better quality of service (QoS) to the users. Additionally, load-based resource allocation can help to improve the overall capacity of the network by allowing more devices to communicate simultaneously. These metrics can be used to compute the overall network efficiency in D2D communication. The higher the data rate, link reliability, and latency, the higher the overall network efficiency. Algorithm 1 expresses the functions of load-based resource optimization.

Algorithm 1: Load-based resource optimization algorithm

1. Start
2. Get the user resource request (URR);
3. Send the request to the network load manager (NLM)
4. If (load = balanced)
5. Then, check if (resource = available)
6. Allot the required resource as per the availability;
7. Else wait the next slot for available resource;
8. Forward the request into the queue;
9. Go to step 3;
10. Else go to step 8;
11. End

The following Figure 2 expresses the flow diagram of the proposed model. Here, the resources, such as energy, power, bandwidth, or spectrum, are assigned as per the user's requirements.

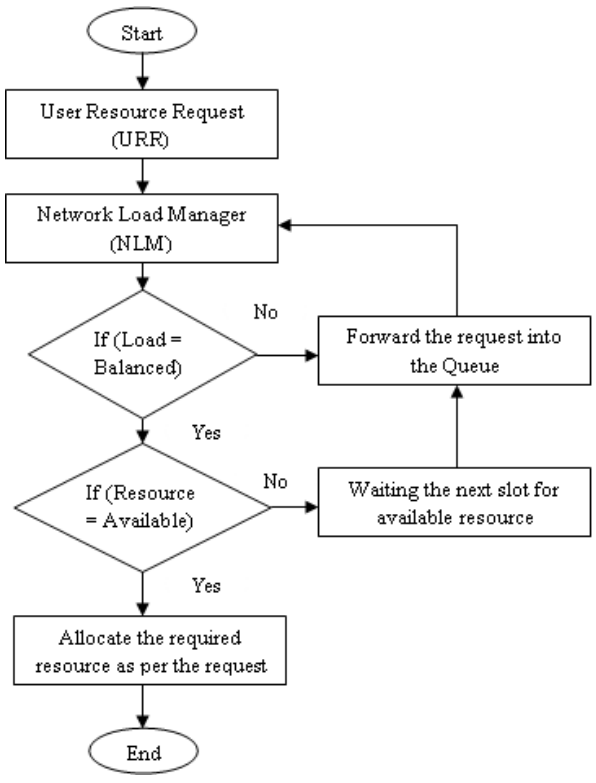


Figure 2. Proposed flow diagram.

This can help to reduce the overall costs associated with maintaining the network. Network efficiency in device-to-device (D2D) communication can be computed through the use of metrics such as data rate, link reliability, and latency.

- Data rate: This metric measures the amount of data that can be sent over a given period. It is usually measured in bits per second (bps).

- Link reliability: This metric measures the probability that a packet of data will be successfully delivered between two devices. It is usually measured in terms of packet delivery ratio (PDR).
- Latency: This metric measures the time taken for a data packet to travel from one device to another. It is usually measured in milliseconds (ms).

Assigns resources based on user needs: Load-based resource allocation allows the network to assign resources to users based on their individual needs. The network admin assigns the resources as per the request from the device. This helps to ensure that users obtain the resources they need to achieve their desired goals.

Improves network efficiency: Load-based resource allocation improves network efficiency by automatically allocating resources according to the load and traffic. This helps to reduce the amount of wasted network resources and improve network performance.

Increases network scalability: By enabling the network to dynamically allocate resources according to user demand, load-based resource allocation increases the scalability of the network. This allows the network to handle larger numbers of users and devices, as well as more intensive applications.

Enhances user experience: By providing users with the resources they need, load-based resource allocation helps to enhance the user experience. This can lead to higher levels of user satisfaction, which can help to promote the network.

Improves overall system performance: By ensuring that the right resources are allocated to the right users at the right time, load-based resource allocation helps to improve the overall performance of the system. This can help to improve the efficiency and reliability of the network.

The load-based optimization model helps to overcome resource allocation constraints in device-to-device communication in 5G-WPAN by optimizing the resources allocated to each device based on their current load. This model helps to ensure that devices are not over- or under-utilizing their resources, as it dynamically adjusts the amount of resources allocated to each device according to their current load. This helps to ensure that each device can access the resources it needs to perform its tasks without competing for resources with other devices. In addition, this model helps to reduce latency and improve the overall performance of the network.

4. Analytical Discussion

Load-based resource allocation in a device-to-device communication network is a method of allocating resources in a communication network between multiple devices to optimize performance. Let us consider the different array of devices that communicate with each other in networks. The access request is shown in Equation (1).

$$L = \{L_1, L_2, L_3 \ldots \ldots L_n\} \tag{1}$$

The request completion duration (d_t) with the request of a different vector (β) provides the occurrence capacity (C_z) in the occurrence number (I_z). Where μ is the task completion duration and α is the cost of service (CoS). Finally, the x denotes the overall cost to complete the service. Now, the objective function (F) here provides the service requests for each device. This is expressed in the following Equation (2):

$$F = \min \mu \ln(\beta d_t) + \alpha \ln x \tag{2}$$

$$\sum_{z \in T_e} C_z \times I_z > l_p \tag{3}$$

where the values of μ and $\alpha < 0$; then, Equation (4) can be the following:

$$\mu + \alpha = 1 \tag{4}$$

$$L = x_{valid} = \sum_{z=1}^{N} O_z \times I_z \tag{5}$$

where the valid user loads are accommodated in the network with the occurrence price (O_z) and the occurrence number (I_z). The entire load calculation is completed at a particular time (T_z), and the number of devices are functioning in the network. This is shown in the following Equation (6):

$$L = x_{valid} = \sum_{z=1}^{N} O_z \times I_z \times T_z \tag{6}$$

Now, the primary user load (L_{PU}) and c secondary user load (L_{SU}) can be computed with the help of the below computations:

$$L_{PU} = \{ax_1 + ax_2 + ax_3 + \ldots\ldots + ax_n\} \tag{7}$$

$$L_{SU} = \{by_1 + by_2 + by_3 + \ldots\ldots + by_n\} \tag{8}$$

The total load can be computed with the help of the following Equation (9):

$$L = L_{PU} + L_{SU} \tag{9}$$

$$L = \{ax_1 + ax_2 + ax_3 + \ldots\ldots + ax_n\} + \{by_1 + by_2 + by_3 + \ldots\ldots + by_n\} \tag{10}$$

Now, the load-based resource allocation has been performed based on the user's request. The combination of bandwidth utilization (B_x), memory allocation (M_x), and capacity allocation (C_x) is called resource allocation. All the resources are allocated with the cost coefficient 'u'. This is shown in Equation (11):

$$L = (u_1 \times B_x) + (u_2 \times M_x) + (u_3 \times C_x) \tag{11}$$

$$u = u_1 + u_2 + u_3 = 1 \tag{12}$$

This is performed by monitoring the load placed on each device in the network and dynamically allocating resources, such as bandwidth, processing power, memory, and energy, based on the current load on each device. This ensures that each device in the network receives the resources it needs to operate optimally and efficiently while avoiding resource contention and wasted resources.

4.1. Improved Efficiency

Load-based resource allocation allows for efficient distribution of resources in device-to-device communication. This ensures that resources are evenly distributed and utilized by each device, which helps to improve the overall efficiency. There are many benefits to using load-based resource allocation. One of the most important benefits is that it can help to improve network efficiency. This is because it ensures that resources are used efficiently and that they are not wasted. Additionally, load-based resource allocation can help to improve communication between devices by making sure that they are using the resources they need to communicate effectively. Overall, load-based resource allocation is an important resource allocation strategy that can help to improve network efficiency. It is important to make sure that resources are used efficiently and that communication between devices is improved.

4.2. Reduced Congestion

Load-based resource allocation helps to prevent network congestion by allocating resources based on the current network load. This can help to reduce latency and improve

overall network performance. There are many potential benefits of reduced congestion in device-to-device communication. One potential benefit is that it could lead to improved communication quality. Another potential benefit is that it could lead to reduced energy consumption, as devices would not need to transmit as often. Additionally, reduced congestion could lead to improved network performance overall, as there would be fewer collisions and less contention for resources.

4.3. Maximized Performance

By allocating resources based on the current network load, devices can maximize their performance. This can help to improve user experience and provide a better overall experience. There are various ways to maximize performance in device-to-device communication. One way is to ensure that devices are properly configured and compatible with one another. Another way is to optimize the communication protocols that are used. A further way is to use techniques such as load balancing and quality of service (QoS) to manage traffic and improve performance.

4.4. Increased Scalability

Load-based resource allocation allows for increased scalability in device-to-device communication. This means that as the number of devices increases, resources can be allocated accordingly, allowing for a more scalable communication system. The scalability of device-to-device communication has improved significantly in recent years, thanks to advances in technology. This has made it possible for more devices to communicate with each other seamlessly and with less interference. One of the main reasons for this improved scalability is the development of new communication protocols that are specifically designed for device-to-device communication. These protocols can make better use of the available bandwidth and resources, which results in improved communication performance. Another reason for the improved scalability of device-to-device communication is the increasing number of devices that are equipped with the necessary hardware and software to support this type of communication. This includes both the number of devices that can connect to a network and the number of devices that can communicate with each other directly. The improved scalability of device-to-device communication has numerous benefits. It allows for more efficient use of resources, improved communication performance, and better connectivity between devices. This, in turn, can lead to improved productivity, reduced costs, and improved user experience.

4.5. Impacts of SINR

The impact of SINR on a load-based optimization model for device-to-device (D2D) communication in a 5G-WPAN (Wireless Personal Area Network) can be significant. The SINR (Signal-to-Interference-plus-Noise Ratio) is a critical factor in determining the performance of D2D communication and directly impacts the optimization model. A higher SINR means better communication performance, while a lower SINR leads to degraded communication performance. The SINR impacts the optimization model because it affects the selection of optimal transmission parameters, such as the power levels and modulation schemes. A high SINR can allow higher data rates and increased reliability, enabling more efficient utilization of the available bandwidth and resources. A low SINR, on the other hand, leads to lower data rates, higher error rates, and a greater need for error correction and retransmission. The SINR also affects the optimization model by influencing the overall network capacity. In a 5G-WPAN, the network capacity can be limited by the SINR since a lower SINR leads to a lower overall capacity. It can lead to a more stringent reduction in interference between devices. As the SINR increases, the interference between the devices decreases, thus increasing the throughput and efficiency of the communication. Additionally, higher SINR values can reduce the power consumption of the devices, which can also improve the overall performance of the communication. Finally, higher SINR values can also reduce the data transmission latency, improving communication performance.

The user should provide the base station with information regarding their current resource usage and expected future resource usage. The base station can then use this information to determine how to optimally allocate resources to maximize overall efficiency while minimizing user power consumption. Additionally, the base station can provide feedback to the user in the form of load-based resource optimization advice. This can be performed through automated or manual means, depending on the user's preferences. The user should also provide the base station with any preferences or restrictions regarding resource allocation. The user can be controlled by the base station in two ways:

- The base station can send commands to the user's device to adjust the usage of resources such as power, bandwidth, and memory to optimize the system performance.
- The base station can also provide instructions to the user regarding which applications and activities are allowed or not allowed to optimize the system performance. Mobility management enables devices to move between networks and access points without losing connection and data. The primary practice of mobility-aware D2D communications is to leverage technologies such as low-power wide-area networks (LPWANs) and multi-hop mesh networks.

5. Comparative Analysis

The proposed load-based resource optimization model (LBROM) has been compared with the existing traffic-shifting-based resource optimization (TSRO), joint resource optimization (JRO), and multirate throughput optimization (MTO). Here, the network simulator v.2.0 has the software used to simulate the results. The simulation setup is shown in the following Table 2.

Table 2. Simulation Setup.

Parameter	Value
S_a (simulation area)	1250 m × 1250 m
SIFS (short inter-frame space)	18 s
DR_t (transmission data rate)	15 Mbps
DR_i (interference detection rate)	28 ms
T_s (slot time)	14 ms
B_{sc} (sub-channel bandwidth)	820 GHz
B_s (system bandwidth)	16 MHz
F_c (carrier frequency)	11.4 MHz
T_d (simulation duration)	28 s

5.1. Computation of Network Efficiency

Load-based resource allocation allows for improved network efficiency by dynamically allocating resources to devices based on the current load. This ensures that devices receive a fair share of the available resources, instead of being allocated a fixed amount. Load-based resource allocation is a resource allocation strategy that is based on the principle of allocating resources to devices based on their current load. This approach is designed to improve network efficiency by making sure that resources are used efficiently. The network efficiency can be computed with the help of the following Equation (13):

$$E_n = \left(\frac{D_t - D_{rt}}{D_t}\right) \times 100\% \tag{13}$$

where E_n represents the network efficiency. The D_t indicates the transmitted data and D_{rt} represents the retransmitted data.

Figure 3 shows the comparison of network efficiency between the existing and proposed models. In a comparison range, the existing traffic-shifting-based resource optimization (TSRO) obtains 64.68%, joint resource optimization (JRO) reaches 72.12%, multirate throughput optimization (MTO) reaches 51.92% network efficiency, and the proposed load-based resource optimization model (LBROM) achieves 86.00% network efficiency. Device-to-device (D2D)

communication networks have become increasingly popular due to their ability to efficiently utilize resources and provide high-speed data transfer. The efficiency of a D2D network is determined by its ability to utilize resources efficiently and to provide a reliable connection between devices. Efficiency can be measured by the amount of data transferred per unit of time, the latency of the connection, and the overall throughput of the network. Additionally, the reliability of the connection and the power consumption of the devices can also be considered when measuring the efficiency of a D2D network.

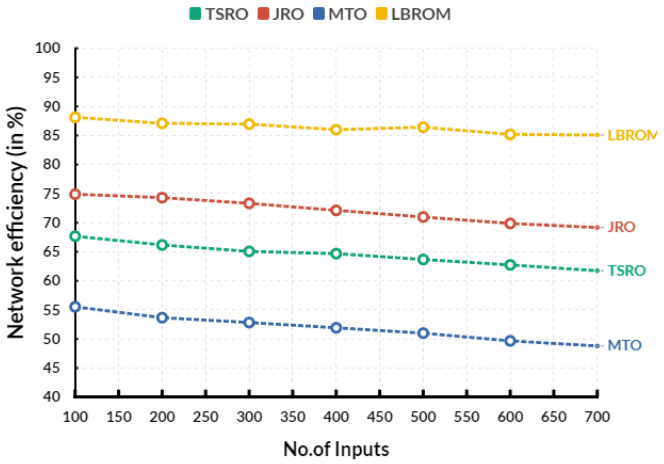


Figure 3. Comparison of network efficiency.

5.2. Computation of Throughput

By allocating resources to devices based on the current load, load-based resource allocation can increase the overall throughput of the network. This is because more resources are given to devices that require them, resulting in better overall performance. The network throughput can be computed with the help of the following Equation (14):

$$T = \left(\frac{S_p}{T_{RT}}\right) \times \left(\frac{1.2}{\sqrt{L_p}}\right) \tag{14}$$

where T represents the throughput of the network. S_p represents the size of the transmitted message packet. T_{RT} indicates the round-trip time and L_P means the packet loss.

Figure 4 shows the comparison of throughput between the existing and proposed models. In a comparison range, the existing traffic-shifting-based resource optimization (TSRO) obtains 78.24%, joint resource optimization (JRO) reaches 85.85%, multirate throughput optimization (MTO) reaches 55.78% throughput, and the proposed load-based resource optimization model (LBROM) achieves 93.74% throughput. Throughput in device-to-device communication can be calculated by dividing the amount of data successfully transferred in a certain period by the total amount of data that was attempted to be transferred at the same time. Generally, throughput is expressed in bits per second (bps).

5.3. Computation of Reduced Latency

By allocating resources to devices based on the current load, load-based resource allocation can reduce latency. This is because devices that require more resources are allocated more resources, which can help to reduce the delay experienced by users. The network latency can be computed with the help of the following Equation (15):

$$L = \left(\frac{D_t}{S_t}\right) + \left(\frac{S_p}{R_t}\right) \tag{15}$$

where L denotes the network latency. The D_t represents the transmission distance and S_t has indicate the transmission speed. The S_p indicates the packet size and R_t indicates the transmission rate.

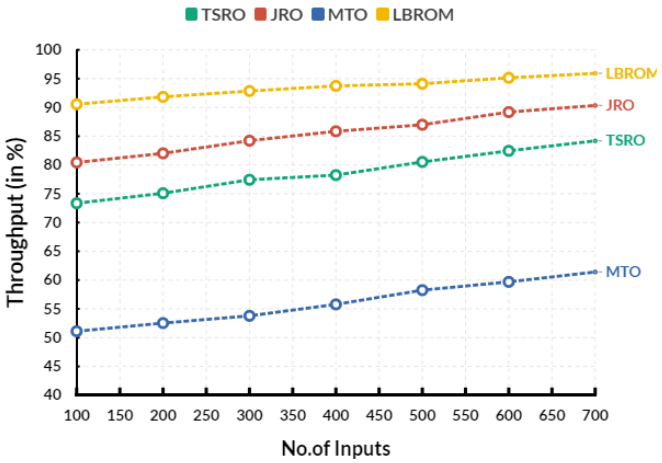


Figure 4. Comparison of network throughput.

Figure 5 shows the comparison of reduced latency between the existing and proposed models. In a comparison range, the existing traffic-shifting-based resource optimization (TSRO) obtains 67.08%, joint resource optimization (JRO) reaches 83.78%, multirate throughput optimization (MTO) reaches 63.16% reduced latency, and the proposed load-based resource optimization model (LBROM) achieves 91.94% reduced latency. In device-to-device communication network, this refers to the amount of time needed for data to travel through a network from one device to another. It is measured in milliseconds (ms), which is one-thousandth of a second. Reducing latency can significantly improve network performance, allowing for faster data transfer between devices and more efficient communication.

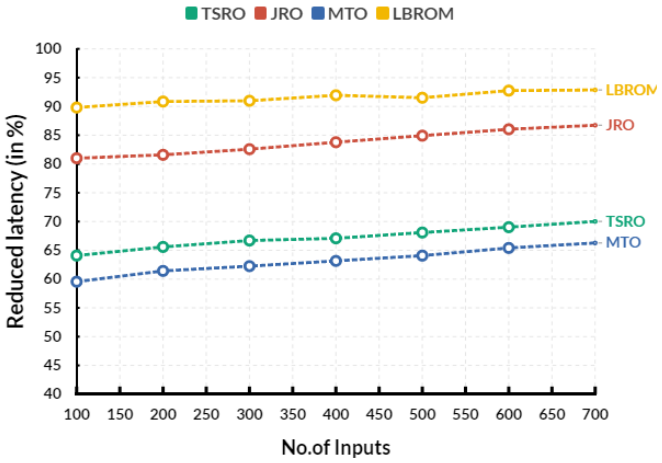


Figure 5. Comparison of reduced latency.

5.4. Computation of Scalability

Load-based resource allocation can help to improve scalability in a device-to-device communication network. This is because resources are allocated based on the current load, allowing for more efficient use of existing resources. This helps to ensure that the network can handle increasing numbers of devices without becoming overwhelmed. The scalability has been computed with the help of the following Equation (16):

$$S(n) = \frac{n}{1 + \alpha(n-1) + \beta n(n-1)} \tag{16}$$

where S denotes the scalability of the network and 'n' refers to the number of nodes. The 'α' represents the contention of the nodes and 'β' indicates the coherency constant.

Figure 6 shows the comparison of scalability between the existing and proposed models. In a comparison range, the existing traffic-shifting-based resource optimization (TSRO) obtains

69.38%, joint resource optimization (JRO) reaches 80.38%, multirate throughput optimization (MTO) reaches 60.42% scalability, and the proposed load-based resource optimization model (LBROM) achieves 92.85% scalability. Device-to-device communication networks are characterized by their scalability, which refers to the ability of the network to accommodate growth in the number of nodes or devices connected to it. Scalability is an important feature for any network, as it allows for a larger number of devices to communicate without reducing the network's performance. This is especially important for networks that support a large number of devices, such as the Internet of Things (IoT). For a device-to-device communication network to be scalable, it must be able to accommodate an increase in the number of devices connected to it, while still providing the same level of performance. Table 3 provides the overall comparison between the existing and proposed models.

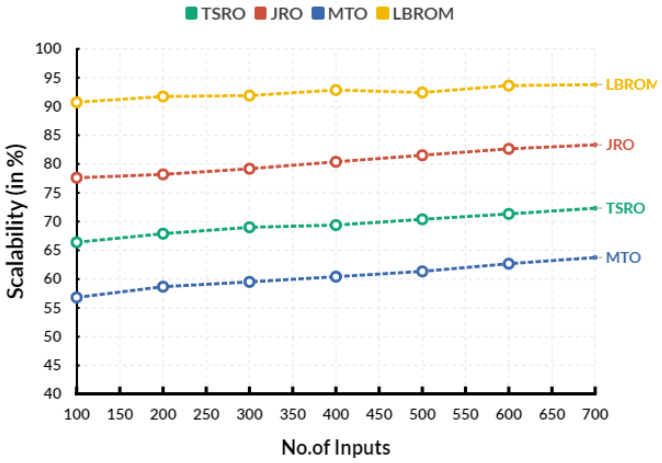


Figure 6. Comparison of scalability.

Table 3. Comparison of scalability (in %).

Parameters	TSRO	JRO	MTO	LBROM
Network efficiency	64.68	72.12	51.92	86.00
Throughput	78.24	85.85	55.78	93.74
Reduced latency	67.08	83.78	63.16	91.94
Scalability	69.38	80.38	60.42	92.85

In a comparison range, the proposed load-based resource optimization model (LBROM) can achieve 86.00% network efficiency, 93.74% throughput, 91.94% reduced latency, and 92.85% scalability. The load-based resource allocation in device-to-device communication networks works by allocating resources based on the current load of the network. This helps to ensure that resources are used efficiently and that all devices have an equal opportunity to access the network. The load-based resource allocation algorithm determines which devices should have access to the network, and how much network access each device should have based on the current load. This helps to ensure that devices do not overload the network and that each device can use the network as efficiently as possible. If the device is not able to connect to the central base station nearby, then we can configure the topology. The solution to resolve this issue for device-to-device communication in 5G-WPAN is to use a mesh-topology-based network infrastructure. These infrastructures allow devices to communicate directly with one another, without relying on a central base station. This would allow the devices to communicate with each other in the absence of a central base station, enabling device-to-device communication. Mesh networks have been widely used in many different technologies, such as Wi-Fi, mobile data networks, and now in 5G-WPAN networks. 5G-WPAN is designed to enable device-to-device communication by utilizing the existing infrastructure of routers and other nodes to create an interconnected mesh of devices. This allows for seamless communication between devices that are

within range of each other and connected to the same router nodes. To accomplish this, communication between devices should be established through the router nodes, allowing data to be transferred between devices without having to establish a direct connection. This type of communication is especially useful for applications such as home automation, IoT, and mobile devices.

The way to optimize and efficiently resource calls for device-to-device communication in 5G-WPAN is by using advanced scheduling and routing. Such techniques can be used to decrease the amount of energy required for a given communication session by making the most efficient use of available resources. Additionally, advanced protocols such as IEEE 802.15.4e can be used to reduce the number of hops required for a given communication session. This further reduces the overall energy consumption required for the given communication session. Additionally, 5G-WPAN can also be configured to use various frequencies hopping and power control techniques to reduce interference, and to ensure that each device is using the most efficient frequency for its communication session.

6. Conclusions

A device-to-device (D2D) communication network is a type of network in which communication occurs directly between devices without the need for an intermediate base station. In a D2D network, each device acts as both a transmitter and a receiver, allowing for communication with any other device in the network. D2D communication can be used for a variety of applications, including file sharing, gaming, and social networking. One of the key benefits of D2D communication is that it can be used to offload traffic from the cellular network. By allowing devices to communicate directly with each other, D2D can reduce the amount of traffic that needs to be routed through the cellular network, freeing up bandwidth for other users. The proposed model achieves 86.00% network efficiency, 93.74% throughput, 91.94% reduced latency, and 92.85% scalability. The proposed load-based resource allocation is a type of resource allocation in which the amount of resources allocated to a particular task is based on the amount of work that needs to be done. In a D2D communication network, load-based resource allocation can be used to dynamically allocate resources based on the needs of the devices in the network. If two devices are sharing a file, the amount of resources allocated to the file transfer will be based on the file size and the number of devices that are trying to access the file. If the file is large or many devices are trying to access it, more resources will be allocated to the transfer. Load-based resource allocation is an important tool for managing D2D communication networks because it allows for the efficient use of resources. By allocating resources based on the needs of the devices in the network, load-based resource allocation can help to ensure that D2D communication is as efficient as possible.

Author Contributions: Conceptualization, J.L. and T.K.; methodology, J.L. and R.K.; investigation, A.A. and L.V.; writing—original draft preparation, J.L., T.K. and R.K.; writing—review and editing, J.L., N.A. and L.V.; formal analysis, A.A.A. and J.L.; software, A.A., N.A. and T.K.; visualization, A.A. and T.K.; All authors have read and agreed to the published version of the manuscript.

Funding: The authors are thankful to the Deanship of Scientific Research at Najran University for funding this work under the Research Groups Funding program grant code (NU/RG/SERC/12/9).

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Chapnevis, A.; Güvenç, I.; Bulut, E. Traffic shifting based resource optimization in aggregated IoT communication. In Proceedings of the 2020 IEEE 45th Conference on Local Computer Networks (LCN), Sydney, Australia, 16–19 November 2020; pp. 233–243.
2. Chai, R.; Wang, P.; Huang, Z.; Su, C. Network lifetime maximization based joint resource optimization for wireless body area networks. In Proceedings of the 2014 IEEE 25th Annual International Symposium on Personal, Indoor, and Mobile Radio Communication (PIMRC), Washington, DC, USA, 2–5 September 2014; pp. 1088–1092.
3. Ercetin, O. Association games in IEEE 802.11 wireless local area networks. *IEEE Trans. Wirel. Commun.* **2008**, *7*, 5136–5143. [CrossRef]

4. Zhang, J.; Han, G.; Qian, Y. Queuing theory based co-channel interference analysis approach for high-density wireless local area networks. *Sensors* **2016**, *16*, 1348. [CrossRef] [PubMed]
5. Hui, J.W.; Culler, D.E. Extending IP to low-power, wireless personal area networks. *IEEE Internet Comput.* **2008**, *12*, 37–45. [CrossRef]
6. Mc Gibney, A.; Klepal, M.; Pesch, D. A wireless local area network modeling tool for scalable indoor access point placement optimization. In Proceedings of the 2010 Spring Simulation Multiconference, Orlando, FL, USA, 11–15 April 2010; pp. 1–8.
7. Gu, D.; Zhang, J. A new measurement-based admission control method for IEEE802. 11 wireless local area networks. In Proceedings of the 14th IEEE Proceedings on Personal, Indoor and Mobile Radio Communications, 2003. PIMRC 2003, Beijing, China, 7–10 September 2003; Volume 3, pp. 2009–2013.
8. Logeshwaran, J.; Shanmugasundaram, N.; Lloret, J. L-RUBI: An efficient load-based resource utilization algorithm for bi-partite scatternet in wireless personal area networks. *Int. J. Commun. Syst.* **2023**, *36*, e5439. [CrossRef]
9. Kuo, Y.L.; Lai, K.W.; Lin, F.Y.S.; Wen, Y.F.; Wu, E.H.K.; Chen, G.H. Multirate throughput optimization with fairness constraints in wireless local area networks. *IEEE Trans. Veh. Technol.* **2008**, *58*, 2417–2425.
10. Qiao, J.; Cai, L.X.; Shen, X.S.; Mark, J.W. Enabling multi-hop concurrent transmissions in 60 GHz wireless personal area networks. *IEEE Trans. Wirel. Commun.* **2011**, *10*, 3824–3833. [CrossRef]
11. Laghari, M.B.; Shahwani, H.; Shah, S.A.; Wagan, R.A.; Rauf, Z.; Ali, I.; Alshamrani, S.S.; Frnda, J. Towards enabling multihop wireless local area networks for disaster communications. *Wirel. Commun. Mob. Comput.* **2021**, *2021*, 5540480. [CrossRef]
12. Kumar, V.; Tiwari, S. Routing in IPv6 over low-power wireless personal area networks (6LoWPAN): A survey. *J. Comput. Netw. Commun.* **2012**, *2012*, 316839. [CrossRef]
13. Obelovska, K.; Panova, O.; Karovič, V., Jr. Performance analysis of wireless local area network for a high-/low-priority traffic ratio at different numbers of access categories. *Symmetry* **2021**, *13*, 693. [CrossRef]
14. Bosio, S.; Capone, A.; Cesana, M. Radio planning of wireless local area networks. *IEEE/ACM Trans. Netw.* **2007**, *15*, 1414–1427. [CrossRef]
15. Purandare, R.; Ratnaparkhi, A.; Bang, A. Resource Optimization using the Taguchi Technique for Channel Allocation. *Int. J. Intell. Syst. Appl. Eng.* **2023**, *11*, 93–99.
16. Lima, M.P.; Takahashi, R.H.; Vieira, M.A.; Carrano, E.G. Multiobjective planning of indoor Wireless Local Area Networks using subpermutation-based hybrid algorithms. *Knowl. Based Syst.* **2023**, *263*, 110293. [CrossRef]
17. Pawar, R.S.; Kalbande, D.R. Optimization of quality of service using ECEBA protocol in wireless body area network. *Int. J. Inf. Technol.* **2023**, *15*, 595–610. [CrossRef]
18. Radha, P.; Subadra, M.S. Ensemble Learning Based Multiple Mobile Sink Architecture For Energy Efficient Wireless Body Area Network Towards Disease Centric Patient Group Data Management. *J. Pharm. Negat. Results* **2023**, *13*, 7096–7107.
19. Alani, T.O.; Al-Sadi, A.M. Survey of optimizing dynamic virtual local area network algorithm for software-defined wide area network. *Telecommun. Comput. Electron. Control* **2023**, *21*, 77–87. [CrossRef]
20. Liu, R.; Wu, W.; Zhao, Z.; Ding, X.; Zhou, D.; Zhang, Y. Coordinated planning transmission tasks in heterogeneous space networks: A semi-distributed approach. *China Commun.* **2023**, *20*, 261–276. [CrossRef]
21. Nayakwadi, N.; Fatima, R. Resource optimization-based network selection model for heterogeneous wireless networks. *IAES Int. J. Artif. Intell.* **2023**, *12*, 357. [CrossRef]
22. Xiao, H.; Cai, L.; Feng, J.; Pei, Q.; Shi, W. Resource Optimization of MAB-based Reputation Management for Data Trading in Vehicular Edge Computing. *IEEE Trans. Wirel. Commun.* **2023**, 1. [CrossRef]
23. Das, S.K.; Benkhelifa, F.; Sun, Y.; Abumarshoud, H.; Abbasi, Q.H.; Imran, M.A.; Mohjazi, L. Comprehensive Review on ML-based RIS-enhanced IoT Systems: Basics, Research Progress and Future Challenges. *Comput. Netw.* **2023**, *224*, 109581. [CrossRef]
24. Van Truong, T.; Nayyar, A. System performance and optimization in NOMA mobile edge computing surveillance network using GA and PSO. *Comput. Netw.* **2023**, *223*, 109575. [CrossRef]
25. Liu, J.; Guo, S.; Wang, Q.; Pan, C.; Yang, L. Optimal multi-user offloading with resources allocation in mobile edge cloud computing. *Comput. Netw.* **2023**, *221*, 109522. [CrossRef]
26. Fu, Y.; Zhang, X.; Qin, X.; Meng, Q.; Huang, B. Data collection of multi-player cooperative game based on edge computing in mobile crowd sensing. *Comput. Netw.* **2023**, *222*, 109551. [CrossRef]
27. Aghapour, Z.; Sharifian, S.; Taheri, H. Task offloading and resource allocation algorithm based on deep reinforcement learning for distributed AI execution tasks in IoT edge computing environments. *Comput. Netw.* **2023**, *223*, 109577. [CrossRef]
28. Zhang, L.; Du, Y. Resilience enhancement scheme for gateway placement in space information networks. *Comput. Netw.* **2023**, *222*, 109555. [CrossRef]
29. Zheng, Z.; Jiang, S.; Feng, R.; Ge, L.; Gu, C. An adaptive backoff selection scheme based on Q-learning for CSMA/CA. *Wirel. Netw.* **2023**, 1–11. [CrossRef]
30. Bi, X.; Sun, X.; Lyu, Z.; Zhang, B.; Wei, X. A back adjustment based dependent task offloading scheduling algorithm with fairness constraints in VEC networks. *Comput. Netw.* **2023**, *223*, 109552. [CrossRef]
31. Haus, M.; Waqas, M.; Ding, A.Y.; Li, Y.; Tarkoma, S.; Ott, J. Security and privacy in device-to-device (D2D) communication: A review. *IEEE Commun. Surv. Tutor.* **2017**, *19*, 1054–1079. [CrossRef]

32. Asadi, A.; Wang, Q.; Mancuso, V. A survey on device-to-device communication in cellular networks. *IEEE Commun. Surv. Tutor.* **2014**, *16*, 1801–1819. [CrossRef]
33. Waqas, M.; Niu, Y.; Li, Y.; Ahmed, M.; Jin, D.; Chen, S.; Han, Z. A comprehensive survey on mobility-aware D2D communications: Principles, practice and challenges. *IEEE Commun. Surv. Tutor.* **2019**, *22*, 1863–1886. [CrossRef]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.