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Channel Assignment Using Mutual Learning Automata in Wireless Mesh Networks

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Abstract

Wireless Mesh Networks (WMN) provide consumers with reliable internet connectivity. By utilizing the Learning Automata for Channel Assignment (LACA), a single router serves multiple users, resulting in significant data traffic within the mesh network. The primary challenge in a multi-channel environment is managing this substantial data flow. This research presents the Mutual Learning Automata-based Channel Assignment (MLACA) Scheme to address this issue. In this framework, Learning Automata (LA) are deployed at adjacent mesh routers, enabling them to collaborate on data transmission and information sharing while learning from their surroundings. The proposed system's collaborative learning automata dynamically adjust channel assignments based on network conditions, enhancing throughput, packet delivery, and spectral efficiency. Performance evaluations using the NS-2 simulator indicate that MLACA significantly outperforms the existing LACA scheme. Specifically, MLACA achieves a 40% increase in throughput, maintains a higher packet delivery ratio even under increased traffic loads, and reduces switching delay by up to 30% compared to LACA. Additionally, MLACA improves effective channel utilization by 25%, increases remaining bandwidth availability by 20%, and enhances the effective transmission rate under dynamic conditions. These results demonstrate that MLACA not only minimizes

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interference and switching overhead but also offers a scalable and efficient solution for real-time channel allocation in dynamic WMN environments.

Keywords: WMN, Channel Assignment, Learning Automata, Network, Data Transmission.

1. Introduction

Wireless Mesh Networks (WMNs) use a mesh topology that allows any node to directly or indirectly communicate with others through multi-hop communication. This decentralized architecture supports peer-to-peer connectivity, enabling nodes to act collaboratively in routing packets across the network [1–3]. Mesh nodes with small radio transmitters use publicly accessible Wi-Fi protocols and operate similarly to wireless routers. The WMN architecture comprises mesh clients, mesh routers, and mesh gateways, offering redundant communication paths and automatic rerouting when links fail, thereby supporting self-configuration and self-healing features [3–5]. In multichannel WMNs, Channel Assignment (CA) is a key operation where radio interfaces are allocated to channels to reduce interference, prevent network partitions, and ensure reliable communication, even during connection disruptions [5]. Traditional CA methods struggle with dynamic challenges such as fluctuating interference levels, node mobility, and varying traffic patterns [6–8]. Additional difficulties include co-channel interference, traffic congestion from uneven load distribution, and poor integration with higher-level protocols [9,10]. The decentralized nature of WMNs further complicates efficient channel assignment, necessitating distributed coordination among nodes [9]. Moreover, due to limited power resources in mesh nodes, energy efficiency becomes critical [11]. Addressing these issues requires adaptive CA algorithms capable of dynamic channel reassignment, interference mitigation, load balancing, cross-layer optimization, and energy-aware operations.

The proposed method uses learning automata to offer a distributed mutual channel allocation and develops a WMN channel allocation algorithm. One advantage of this strategy is that it offers a real-time, topology-independent solution. Wireless networks with several radios and channels may make use of this. In order to achieve maximum utility, the learning automaton continuously acquires the optimal channel selection techniques. The algorithm is very adaptive, particularly to changes in traffic patterns over time. It significantly improves network behavior and strikes a balance between connection and throughput. The novel contribution of the research is as follows:

1. Learning Automata Framework: Nodes select channel allocation actions based on states and transition probabilities, with feedback guiding state transitions.
2. Dynamic Adaptation: Adjusts channel assignments automatically based on evolving network conditions such as interference, traffic patterns, and node mobility.
3. Efficient Resource Consumption: Aims to maximize spectrum usage while minimizing interference, thereby improving network throughput and overall performance.
4. Decentralized Operation: Nodes independently improve channel allocations, ensuring scalability, robustness, and fault tolerance without relying on central control.
5. Iterative Learning Process: Converges to near-optimal solutions through iterative learning, refining channel assignments based on previous experiences.
6. Adaptability: Constantly learns and adapts to changing network conditions through environmental feedback.
7. Fault Tolerance: The decentralized approach reduces the risk of network failures and enhances robustness.
8. Optimized Spectrum Usage: Maximizes resource utilization, minimizing interference, and boosts network reliability.
9. Near-Optimal Solutions: Iterative learning ensures the approach converges to near-optimal channel allocations, improving network efficiency.
10. Reduced Network Congestion: By efficiently managing channel assignments, MLACA helps reduce congestion and transmission delays.

2. Related Work

According to Degan et al. [2], intrinsic congestion issues and high congestion are the causes of the interruptions during channel assignment. Cheng et al. [1] developed a discrete particle swarm optimization-based traffic-independent CA technique. Reducing co-channel interference and determining the most effective approach while the channel is congested are the objectives of this method. Throughout the channel assignment procedure, the issue of radio use was additionally considered. FLMM is the Flow Load Multicast Measure, and FLMMR is the Reliable Flow Load Multicast Metric proposed by Li et al. [9]. When the network is under heavy strain, this technique delivers improved multicast performance. It enhances connectivity and bandwidth consumption. The author also addressed the issue of overlapping channels. Kim et al. [6] suggested a cooperative channel assignment methodology that enhances channel capacity, reduces latency, and diversifies channel routes. It increases network connectivity to boost network capacity. Marina et al. [10] proposed a cluster-based multiple paths topological control and channel allocation method. It is intended to decrease flow dispersion while retaining network connectivity. Kumar et al. [8] introduced the LCM routing measure as a Low-Cost routing Metric. It improves channel capacity and throughput. To enhance performance, an interference-aware channel assignment approach was proposed by Ramachandran et al. [12], although it is not suitable for a static system. Raniwala et al. [13] presented a centralized channel allocation technique. A collaborative learning automata-based routing method and a learning automata technique were proposed by Kumar et al. [8]. The lack of cache coherence and dispersion control is the scheme's fundamental flaw. The proposed scheme overcomes these problems and reduces link failure and delay. Although there are drawbacks, the current techniques for CA in WMN, Fixed Channel Assignment (FCA), are easy to implement but lack the adaptability needed to handle a variety of shifting network conditions [12]. While DCA allows for periodic modifications, it frequently has significant communication latency and complexity, especially in large-scale networks [13]. Furthermore, the distinction between centralized and decentralized systems presents difficulties, with centralized methods facing scalability concerns and decentralized methods necessitating effective coordination mechanisms [14]. In contrast, Mutual Learning Automata for Channel Assignment (MLACA) represents a paradigm shift [15]. Its decentralized operation improves scalability and robustness while reducing dependency on central controllers [16]. MLACA uses machine learning approaches to optimize channel assignments repeatedly, converging to near-optimal solutions while minimizing overhead [17]. Due to the flexibility it offers, MLACA stands out as a potential solution that can adapt to different network topologies and traffic patterns, making it a competitive choice among CA techniques for WMN [18].

Existing Dynamic Channel Assignment (DCA) techniques, while valuable, exhibit significant limitations in scalability, convergence, and overhead, particularly in large-scale and dynamic network environments. Fixed Channel Assignment (FCA) approaches, which are simple to implement, lack the adaptability needed to cope with fluctuating network conditions, making them ill-suited for modern wireless mesh networks (WMNs) [13]. On the other hand, Dynamic Channel Assignment (DCA) techniques provide more flexibility but often introduce high communication latency and complexity due to the need for periodic updates and continuous reconfigurations. This complexity becomes more pronounced in large-scale networks, as Raniwala et al. [13] highlight in their study on centralized channel assignment. Furthermore, centralized methods depend heavily on a central controller, which poses scalability issues as the network grows [1]. Decentralized approaches, although more scalable, suffer from slow convergence and challenges in coordination, particularly in networks with variable traffic and topologies, as discussed by Kim et al. [6] and Tian et al. [14].

The Mutual Learning Automata for Channel Assignment (MLACA) approach addresses these limitations by introducing a decentralized framework that reduces reliance on central controllers, significantly improving scalability. MLACA employs machine learning techniques to continuously optimize channel assignments based on real-time feedback, thus enabling faster convergence and reducing overhead associated with traditional DCA methods [15]. Unlike static systems, MLACA adapts dynamically to network conditions, offering enhanced flexibility and robustness. By minimizing the need for frequent communication exchanges and adapting to network topologies and traffic patterns, MLACA reduces signaling overhead and processing complexity [16]. This ability to adapt in real-time and optimize channel assignments iteratively makes MLACA a promising solution for overcoming the scalability, convergence, and overhead challenges that persist in traditional DCA techniques [17-20].

The novelty of the proposed MLACA technique dynamically adjusts channel assignments based on real-time feedback, significantly reducing interference and maximizing resource use in dynamic situations. It does not require centralized control, providing scalability and resistance to network outages or topology changes. MLACA repeatedly optimizes channel assignments, achieving near-optimal results while minimizing signaling overhead and processing complexity. It is adaptable to different network designs and flows of traffic, making it appropriate for a wide range of uses and deployment situations.

3. Proposed Work

Learning automata in MLACA are made up of states, actions, and related probabilities. At each cycle, nodes in the wireless mesh network choose actions (such as channel allocations) based on their present states and transition probabilities. Feedback from nearby nodes and environmental observations guides state transitions and updates transition probabilities, allowing for long-term learning and adaptability. MLACA converges to near-optimal solutions by iteratively changing channel assignments based on previous experiences and interactions, efficiently minimizing interference, and maximizing resource use in dynamic network situations. Using iterative learning processes, Mutual Learning Automata for Channel Assignment (MLACA) aims to address CA problems in WMNs. The main purposes and objectives of MLACA are as follows.

3.1 Dynamic Adaptation

MLACA aims to automatically modify channel assignments by evolving network circumstances such as interference levels, traffic patterns, and the mobility of nodes.

3.2 Efficient Resource Consumption

The ultimate goal of MLACA is to maximize spectrum consumption while minimizing interference, resulting in improved network throughput, dependability, and overall performance.

3.3 Decentralized Operation

MLACA functions in a decentralized way, allowing network nodes to coordinate without relying on central control. This decentralized method improves scalability, robustness, and adaptation to a variety of network topologies and deployment circumstances.

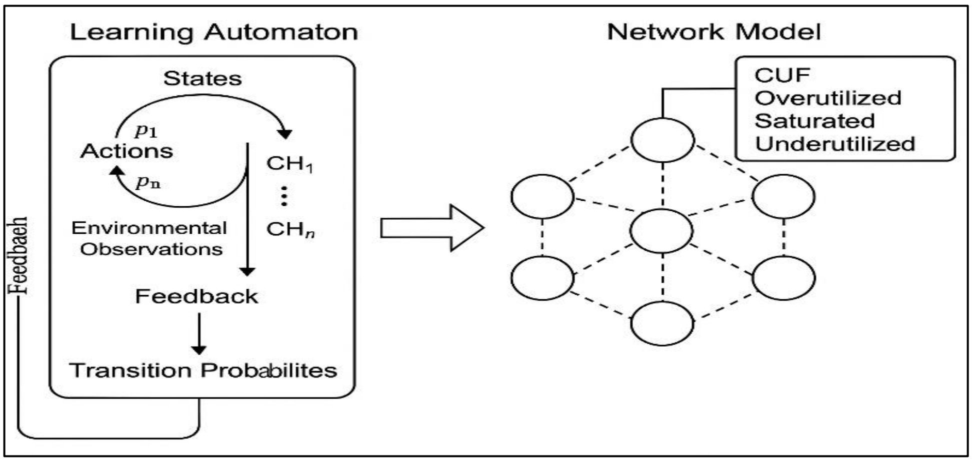

Figure 1. Learning Automata in MLACA

The proposed Mutual Learning Automata for Channel Assignment (MLACA) scheme as shown in Figure 1, utilizes learning automata to make optimal channel allocation decisions in wireless mesh networks (WMNs). Each node in the network operates as an independent learning unit, with states and actions influenced by a Channel Utilization Factor (CUF), which measures the effectiveness of the current channel allocation. The automata update their transition probabilities based on feedback from the environment, such as successful or unsuccessful transmissions. Nodes select actions (channels) probabilistically, and the learning automata adjust their transition probabilities over time based on the feedback, enabling nodes to learn optimal channel allocations in dynamic conditions. The network is modeled as a mesh topology, where nodes communicate with neighboring nodes and adapt their channel assignments based on the CUF, which evaluates whether a channel is overutilized, saturated, or underutilized. Through an iterative feedback process, MLACA minimizes interference and maximizes throughput, gradually converging to near-optimal solutions. The decentralized nature of the system allows each node to act independently without central control, making it scalable and resilient to network topology changes. This approach efficiently handles dynamic network conditions by continuously updating channel allocations based on real-time network feedback.

The probability function takes action by obtaining a reward from its surroundings. The goal is to select the optimal action via continual communication on the device. The best course of action will be chosen through constant interaction with the environment if the algorithm for learning is properly constructed. Consider the selection of channels that are accessible as, $CH_a = \{CH_1, CH_2, \ldots, CH_n\}$. We define the Channel Utilization Factor (CUF) as follows:

$$\text{CUF} = \frac{\sigma^{\text{successful}}}{(\alpha_i \times \beta_i)} \times \eta_i \tag{1}$$

Here, $\sigma^{\text{successful}}$ is the total number of transactions that were successful, α_i and β_i denote the amount of traffic flowing both upward and downward over the MR, and η_i is the average transmission rate across the channel. Each of the channel states are calculated using the following equation.

$$C^{\text{states}}_i = \begin{cases} \text{CUF} > \text{thr, overutilized} \\ \text{CUF} = \text{thr, saturated} \\ \text{CUF} < \text{thr, underutilized} \end{cases} \tag{2}$$

In this method, every node serves as a learning unit. Each node has the goal of maximizing its reward based on the CUF, as it is measured by it. Using the existing allocated channels, each node in the proposed MLACA algorithm tries to increase the normalized payment in order to enhance its utility factor. Through incremental learning, this technique determines which combination of channels maximizes the utility factor. A node that selects an appropriate channel set during the action it takes is rewarded according to the reward-penalty approach, and the next time slot is adjusted to reflect the likely choice of the action; if no modification occurs, the chosen channel set remains selected. The effective transmission rate is defined as,

$$\eta i=\frac{\mu}{\lambda}(1-Pr^{B}) \tag{3}$$

where Pr^{B} is the blocking probability, μ is the service rate and λ is defined as the request arrival rate. The duration needed to send a packet has been expressed as follows:

$$T_{time}^{C(p)}=2^{i+1}+\frac{p^{size}}{\eta_i}+\frac{CN^{C}}{TS^{C}}\times ST^{C} \tag{4}$$

where, $BT^{C\,(p)}$ is the amount of time MC spends waiting to reach a specific channel C, to transmit the packet p. $TS^{C\,(p)}$ is the amount of time needed for each packet to be transmitted correctly. The time required to detect a collision is $CA^{C\,(p)}$. CN^{C} is the number of collisions for accessing C at a specific time frame. TS^{C} determines how many transmissions or data packets were transmitted over a certain channel C during a specific amount of time, and ST^{C} counts the number of seconds it takes a node to move between channels. Below is an illustration of the total time needed for each packet.

$$T_{time}^{C(p)}=\sum_{p=1}^{z}2^{i+1}+\frac{p^{size}}{\eta_i}+\frac{CN^{C}}{TS^{C}}\times ST^{C} \tag{5}$$

The value for successful transmissions rises as the risk of obstruction and the overall time needed to transfer packets from one location to another decreases. The channel's available bandwidth is calculated as follows.

$$B^{avail}=\frac{CUF}{N^{req}} \tag{6}$$

N^{req} represents the total amount of connections issued by the network router, including upstream and downstream. The available bandwidth is denoted by B^{avail}. Then, equation (6) is rewritten as follows:

$$X_{ij}=\frac{\eta_i}{t^{switch}}\times\frac{CUF}{N^{req}} \quad (7$$

The average cost of the entire procedure is as follows,

$$T_{cost} = (C_{ij}^{req} + C_{ij}^{rep} + C_{ij}^{diss}) \quad (8)$$

The average cost Creqij and Crepij. Cdissij, concerns the average expense of responding to a query result from LA and the typical cost of a LA query request. The cost of transmitting information is represented by the Cdissij. The percentage of requests replied to total requests received is known as the cost of a request.

$$C_{ij}^{rep} = \frac{\mu}{\lambda} \times \text{freq} \quad (9)$$

Learning automata-based channel allocation is a distributed channel allocation technique that allows each node to choose an action on its own for every timeslot. The node does not have to be aware of what is happening around it. Consequently, the suggested method has no dependence on either size or topology. The technique's learning rate is negatively correlated with its complexity. The learning rate is maximized to create a network that is economical. Care must be taken when choosing the rate at which learning occurs if it is set to the utmost, in order to balance computational cost and ideal channel allocation. The cost of response is thus determined by dividing the rate of requests completed by the proportion of requests that arrive with PrB in the case of an interruption. As a result, the related cost may be written as follows.

$$C_{ij}^{rep} = \frac{\mu}{\lambda} \text{Pr}^{B} \times \text{freq} \quad (10)$$

The product of θ^n and CUF yields the cost of data delivery.

$$C_{ij}^{diss} = CUF \times \theta^n \times \text{freq} \quad (11)$$

In the context of wireless communication networks, the total cost usually includes several costs, such as those related to hardware, deployment, operations, and possible fines or losses from system outages or performance problems.

$$T_{cost}=\left(\frac{\mu}{\lambda} + \frac{\mu}{\lambda}\text{PrB} + \text{CUF} \times \theta\text{n}\right)\times\text{freq} \quad (12)$$

Learning automata-based channel allocation is a distributed channel allocation technique that allows each node to choose an action on its own for every timeslot. The node does not have to be aware of what is happening around it. Consequently, the suggested method has no dependence on either size or topology. The technique's learning rate is negatively correlated with its complexity. The learning rate is maximized to create a network that is economical. Care must be taken when choosing the rate at which learning occurs if it is set to the utmost, in order to balance computational cost and ideal channel allocation. The cost of response is thus determined by dividing the rate of requests completed by the proportion of requests that arrive with PrB in the case of an interruption. As a result, the related cost may be written as follows.

In the MLACA framework, mutual learning among neighbouring mesh routers is facilitated through periodic information exchange that allows routers to collaboratively refine their channel allocation strategies. Each mesh router independently observes its local environment, evaluates the performance of available channels based on metrics such as packet delivery success or signal quality, and updates its own probability distribution for channel selection using reinforcement learning principles. To enhance learning and avoid interference, routers communicate with their immediate neighbours to share relevant data, including the currently selected channels, experienced rewards, and their updated probability distributions. This shared information is then integrated using a weighted averaging technique, where each router adjusts its own probability values by incorporating the experiences of its neighbours while maintaining a balance between self-learning and cooperative adaptation. This mutual learning process promotes distributed coordination, improves convergence speed, and enables the network to dynamically adapt to changing traffic patterns and environmental conditions without the need for centralized control.

The mutual learning mechanism among neighbouring mesh routers in the MLACA (Machine Learning-based Adaptive Channel Allocation) algorithm is described as follows.

- **Local Probability Update (per MLACA)**

Each router R_i maintains a probability distribution $P_i = [P_i^1, P_i^2, \dots . P_i^N]$over N channels. After selecting a channel and receiving feedback (reward or penalty), it updates its probabilities:

Reward Update (for selected channel c)

$$P_i^c \leftarrow P_i^c + \alpha.(1 - P_i^c) \tag{13}$$

Penalty Update (for selected channel c)

$$P_i^c \leftarrow P_i^c.(1 - \beta) \tag{14}$$

Update for other channels

$$P_i^j \leftarrow P_i^j.(1 - \alpha) \text{ (if reward) or } P_i^j \leftarrow P_i^j. + \beta\left(\frac{1}{N} - P_i^j\right) \text{ (if penalty)} \tag{15}$$

- **Mutual Learning Fusion**

After exchanging information with its neighbors N_i, router $R_i$integrates the probabilities from each neighboring router $R_i \in N_i$.

$$P_i^c \leftarrow (1-\gamma).P_i^c + \gamma.\frac{1}{|N_i|}\sum_{j\epsilon N_i} P_j^c \tag{16}$$

where:

$\gamma \in (0,1)$ is the mutual learning rate.

$|N_i|$ is the number of neighboring routers.

P_j^c is the probability assigned by neighbor R_j to channel c.

- **Normalization**

After updates, ensure that the probabilities sum to 1:

$$P_i^c \leftarrow \frac{P_i^c}{\sum_{k=1}^{N} P_i^k} \text{ for all c=1,2,..,N} \tag{17}$$

These steps allow each router to learn and adapt based on both its own experience and its neighbors' experiences.

MLACA Algorithm Pseudocode

Initialize:

N ← number of channels

P ← [1/N for i in 1 to N]   // Initial equal probability for all channels

```
  R ← 0                      // Initial reward
  α ← learning rate (0 < α < 1)
  β ← penalty factor (0 < β < 1)
Repeat for each time step t:
  1. Channel Selection:
     Select a channel c_t from {1, 2, ..., N} based on probability distribution P
  2. Sensing and Feedback:
     Sense channel c_t
     If channel c_t is idle (successful transmission):
        reward ← 1
     Else (collision or busy):
        reward ← 0
  3. Reward/Penalty Assignment:
     For each channel i in 1 to N:
        If i == c_t:
           If reward == 1:
              P[i] ← P[i] + α * (1 - P[i])      // Reward update
           Else:
              P[i] ← P[i] * (1 - β)             // Penalty update
        Else:
           If reward == 1:
              P[i] ← P[i] * (1 - α)             // Penalize others during reward
           Else:
              P[i] ← P[i] + β * (1/N - P[i])    // Small compensation
  4. Normalization:
     Normalize P so that ∑P[i] = 1
End Repeat
```

Mutual Learning Automata for Channel Assignment (MLACA) provides significant benefits for optimizing channel assignments in wireless mesh networks (WMNs). For starters, MLACA's capacity for adapting to changing network conditions is a significant advantage. By constantly learning and altering channel assignments based on real-time feedback, MLACA can efficiently reduce interference, accommodate changing traffic patterns, and react to variations in node mobility, assuring optimal network functionality regardless of extremely dynamic contexts. Second, MLACA is decentralized, permitting nodes to independently enhances channel allocations based on regional data and interactions. This decentralized strategy improves scalability, stability, and fault tolerance in large-scale WMNs by eliminating the requirement for centralized control and minimizing single points of failure. Third, MLACA optimizes spectrum usage while minimizing interference, resulting in higher network throughput, reliability, and overall efficiency. Furthermore, MLACA's communication overhead, which is caused by the frequent exchange of information and feedback across network nodes, may contribute to increased network traffic and bandwidth usage, ultimately leading to latency or congestion issues.

4. Result and Discussion

The proposed approach comprises precisely arranging network parameters to replicate and evaluate the efficiency of various channel allocation schemes. Researchers begin by establishing the network topology, which includes the arrangement of nodes and accessible channels. Then, an acceptable channel model is selected that takes into consideration aspects such as signal propagation and interference. Each node is then assigned specialized features, such as transmission range and mobility patterns for mobile applications. The experiment may include evaluating different channel allocation techniques or protocols, such as frequency hopping or dynamic channel assignment. The MLACA algorithm is evaluated using NS-3 on a mesh network of 20–100 routers within a 1000m × 1000m area, using 3–12 wireless channels. Traffic is modeled using CBR or FTP over TCP with varying loads. Key parameters include learning rate (α = 0.1–0.3), penalty rate (β = 0.05–0.2), and mutual learning rate (γ = 0.1–0.3).

The proposed research presents a comparison between the MLACA scheme and the current LACA approach. The performance parameters listed below are assessed:

1. Throughput: The greatest data rate transported from source to destination per unit time is referred to as throughput.

2. Packet Delivery Ratio: The percentage of correctly communicated packets in relation to all transmitted packets is displayed.

3. Switching delay: The duration of time needed for a node or device to toggle between channels of communication is referred to as the switching delay.

4. Channel effective utilization: It is required to find the number of channels used in a specific time frame.

5. V.Remaining Bandwidth: This refers to the ratio of total bandwidth available after incoming requests have been allocated to channels.

4.1 The Impact on the Packet Delivery Ratio

Figures 2 and 3 illustrate the packet delivery ratio, highlighting the effects of modifications to traffic load and traffic flow. Despite increased traffic and throughput, the packet delivery ratio in the MLACA system remains significantly higher than that of the traditional LACA system. Utilizing Channel Utilization Factor (CUF), the LACA framework identifies the most optimal channel. In comparison to the existing LACA structure, the new MLACA model demonstrates an improved packet delivery ratio.

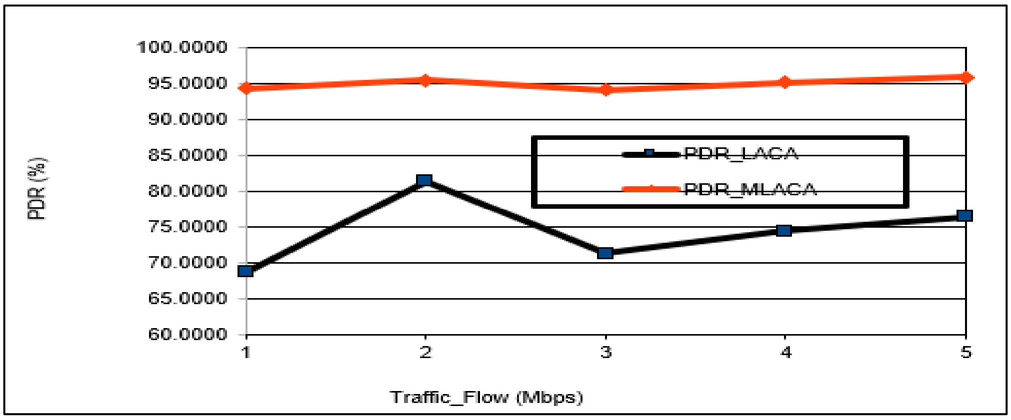

Figure 2. Ratio of Packet Delivery vs. Traffic Flow

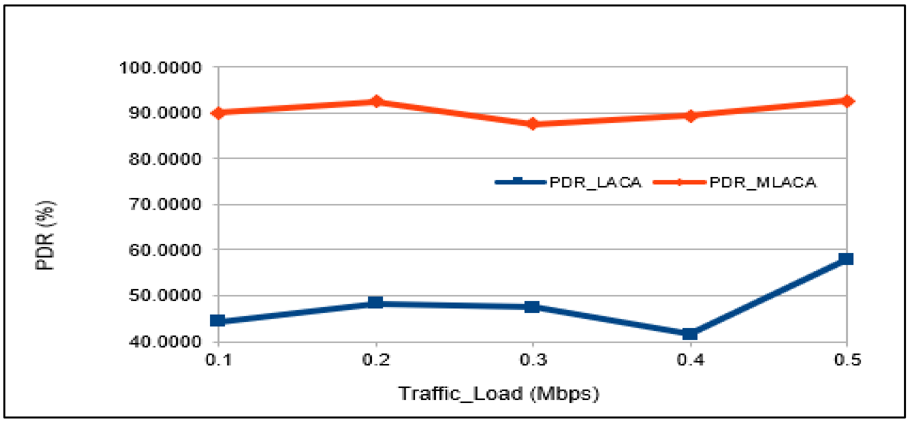

Figure 3. Ratio of Delivery of Packets vs. Traffic Load

4.2 The Effect of Switching Delay

The impact of the recommended approach on switching delay is illustrated in Figure 4 and 5. This may occur when channels are overloaded. Here, LA is used to decide the number of users requesting to switch channels.

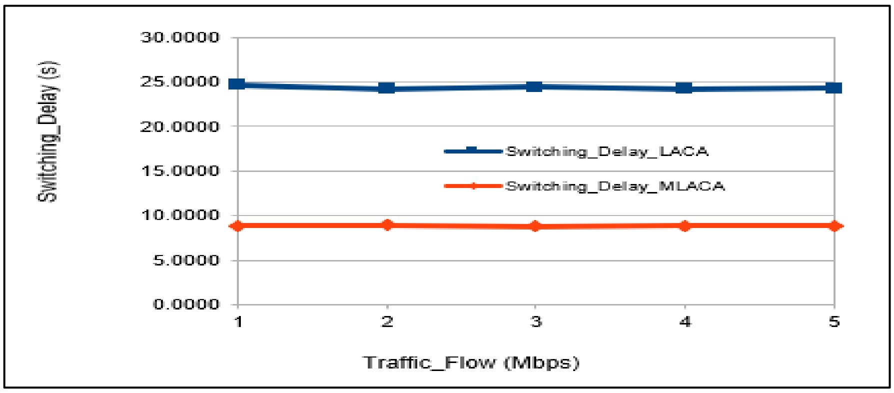

Figure 4. Switching Delay vs. Traffic Flow

In contrast, each MR may retain its queue which is used to make decisions for requests that come in through the use of LA. The switching latency of the proposed structure is less than that of the current system. In the past, LA would go to the next channel if one of the channels became congested. When MLACA is used instead of the current method, illustrated in Figures 5 and 6, the switching latency is reduced.

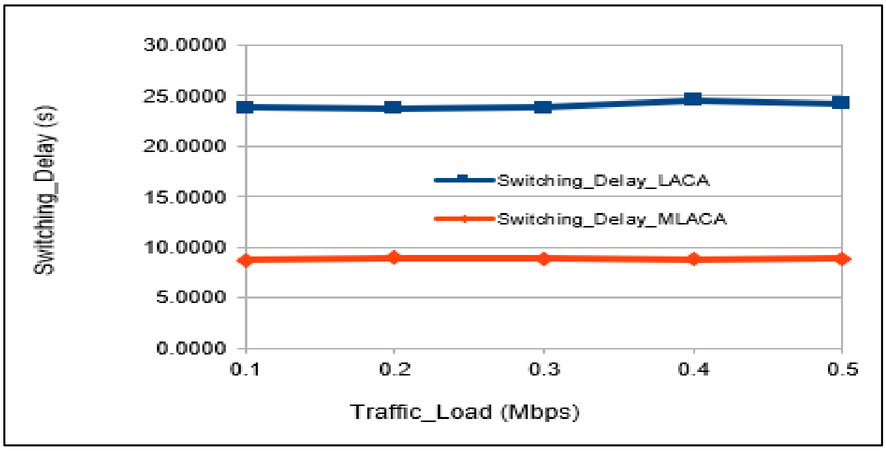

Figure 5. Switching Load vs Delay in Traffic

4.3 Consequence of the Available Bandwidth

Figures 6 and 7 illustrate the impact of the proposed method on the available channel bandwidth following the assignment of requests to a particular channel according to CUF. This allows for the choice of a specific channel and lowers the number of collisions. Network topology is also maintained in this case. The LA oversees and manages the whole procedure.

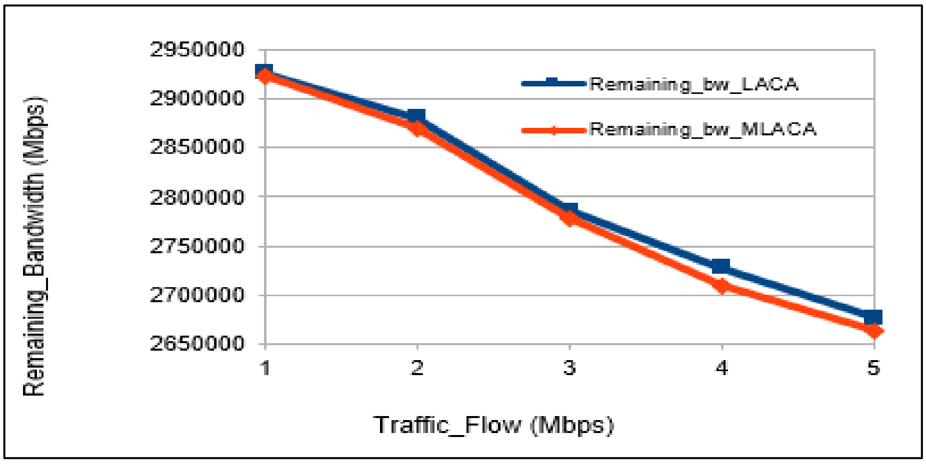

Figure 6. Traffic Flow Against Remaining Bandwidth

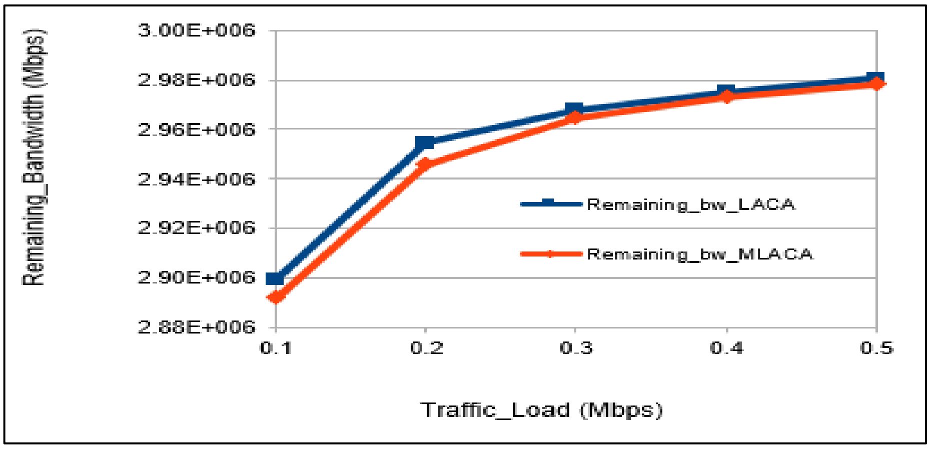

Figure 7. Remaining Bandwidth vs. Traffic Load

4.4 Consequence of the Effective Transmission Rate

As requests arrive and leave on the optimal transmission rate, Figure 8 and Figure 9 show this behaviour.

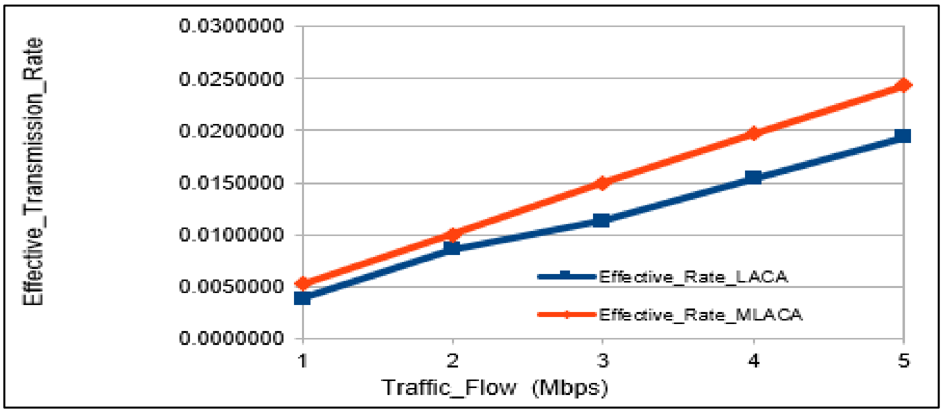

Figure 8. Traffic Flow Versus Effective Transmission Rate

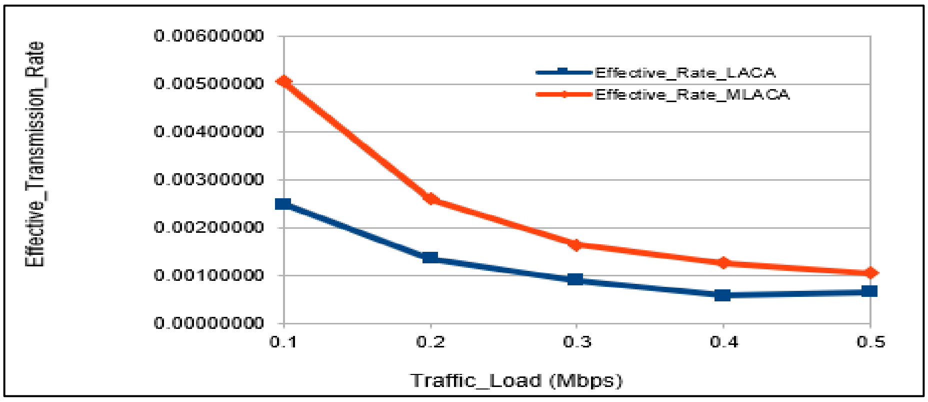

Figure 9. Effective Transmission Rate vs. Traffic Load

The proposed approach has a higher departure rate and faster transmission speed. Every time the departure rate is increased, more traffic is broadcast to the channel. An efficient rate of transmission is generated at an amount greater than LACA when utilizing the MLACA system. In this case, a departure frequency demand yields a better result, resulting in a lower likelihood of traffic flow obstruction. This demonstrates the rate at which channels are effectively utilized.

4.5 Consequence of Effective Channel Utilization

The blocking likelihood decreases as the number of LA and request arrival rates increases as shown in Figures 10 and 11. As a result, effective channel usage increases. If the number of LA is raised, more data from various LAs becomes. In this case, data sharing is done cooperatively via the LA. When the total number of LAs and the requestarrival rate rise, so does the efficiency of bandwidth usage.

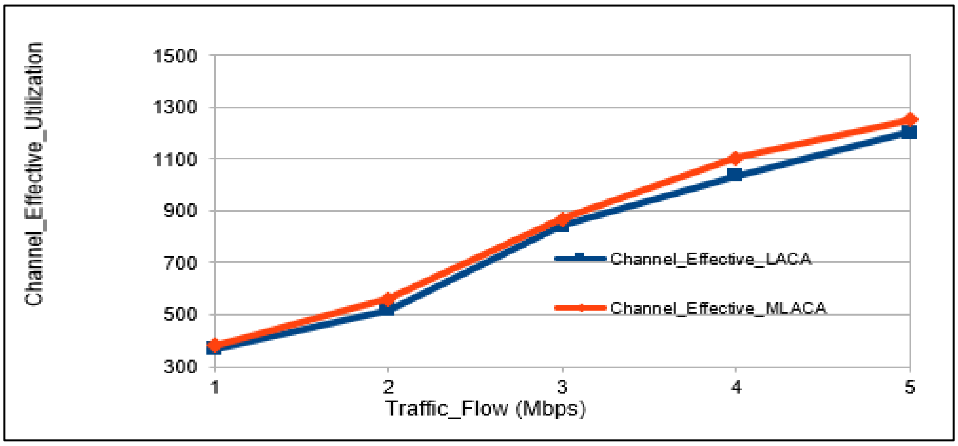

Figure 10. Effective Channel Utilization vs. Traffic Flow

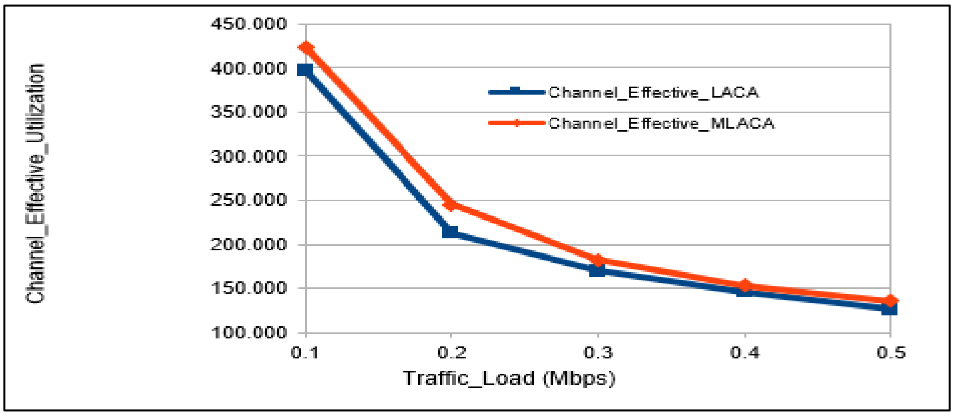

Figure 11. Effective Channel Utilization vs. Traffic Load

4.6 Impact on Throughput

Figures 12 and 13 demonstrate that variations in traffic flow and stress have an impact the throughput of the proposed strategy. The graph shows that throughput improves noticeably for both approaches as traffic volume rises. When it comes to throughput attained with a rise in load, the proposed MLACA technique functions more effectively than the earlier systems. In this instance, the channel cost and the CUF are used by MLACA to carry out the CA. Throughput is increased by 40% in the suggested configuration over the current LACA network. The LACA scheme does not include a channel selection procedure based on load and usage. However, the proposed technique uses a random channel selection. Using the CUF, the LA may determine the optimum channel to allocate a certain channel. This is used to lessen the sources of collisions, resulting in higher throughput.

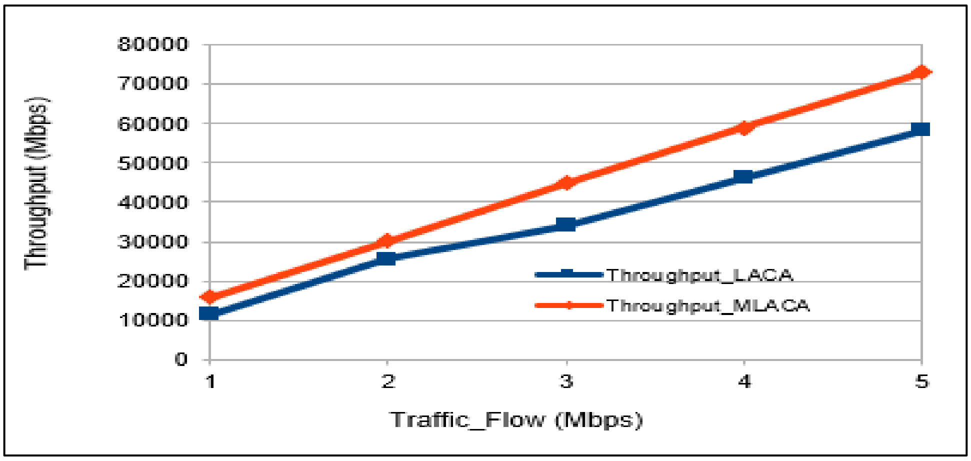

Figure 12. Throughput vs. Traffic Flow

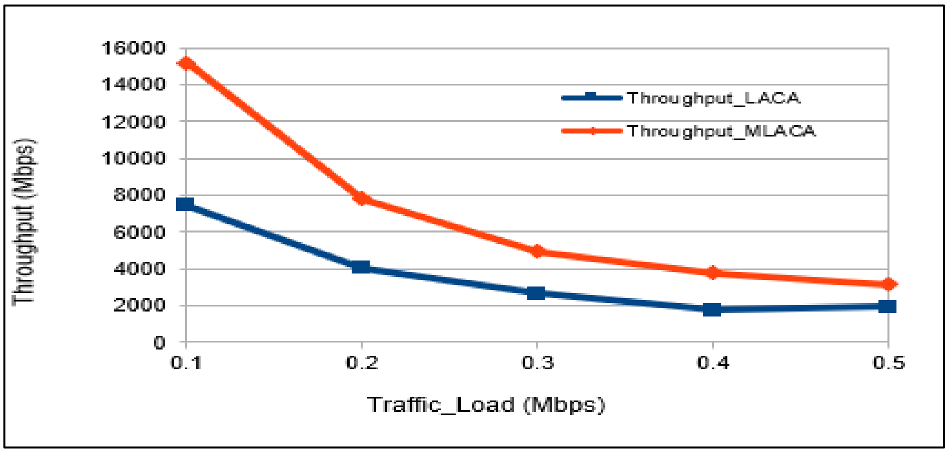

Figure 13. Throughput vs. Traffic Load

The proposed Mutual Learning Automata for Channel Assignment (MLACA) offers a viable method for optimizing CA in WMNs. Through iterative learning processes, MLACA dynamically adapts to changing network circumstances, efficiently minimizing interference and maximizing resource use. This review highlights numerous major discoveries, including MLACA's flexibility to changing situations, decentralized operation, and efficient spectrum usage. MLACA's contributions include its capacity to improve network speed, scalability, and resilience while providing a decentralized and efficient channel assignment method. It effectively addresses key challenges in wireless mesh networks, such as dynamic interference, limited channel availability, and inefficient static channel assignments. By leveraging a learning automata approach with reward and penalty mechanisms, MLACA enables each mesh router to adaptively select the most suitable channel based on past experiences and ongoing network conditions. Additionally, the incorporation of mutual learning among neighboring routers enhances collaborative decision-making, reducing channel conflicts and improving overall network stability. This directly aligns with the research objectives of achieving efficient spectrum utilization, minimizing transmission collisions, and ensuring high throughput and fairness. MLACA's decentralized and adaptive nature allows it to respond quickly to changing traffic patterns and interference levels, fulfilling the goals of scalability, real-time adaptability, and improved quality of service in dynamic wireless environments.

5. Conclusion

In a multichannel context, the proposed approach of collaborative learning automata (CA) offers a streamlined method for determining blocking probability values. At each mobile router (MR), the automation is implemented, with the learning automata (LA) executing CA actions. The environment subsequently provides feedback in the form of either a penalty or a reward. Based on this feedback, the LA adjusts its activities and selects the next course of action. Several performance metrics, including optimal channel utilization, effective transmission rate, switching latency, throughput, and data delivery ratio, were employed to evaluate the approach. The proposed scheme demonstrates that the machine learning-based collaborative automata (MLACA) is a superior alternative to existing methods. Additionally, dynamic network adaptation mechanisms can enhance the resilience of MLACA by allowing it to modify its behavior in real-time in response to network dynamics. Energy efficiency is a critical consideration, driving research into energy-aware MLACA techniques to extend the battery life of wireless mesh network (WMN) nodes. Real-world deployment studies and collaboration with industry stakeholders are essential for validating the practical applicability and scalability of MLACA. Furthermore, standardization initiatives and interoperability guidelines should be pursued to facilitate the seamless integration of MLACA into existing WMN infrastructures. By concentrating on these areas, MLACA has the potential to evolve into a more robust and effective solution, enabling optimal channel assignment and enhanced performance across diverse WMN environments.

References

[1] Cheng, Hongju, Naixue Xiong, Athanasios V. Vasilakos, Laurence Tianruo Yang, Guolong Chen, and Xiaofang Zhuang. "Nodes organization for channel assignment with topology preservation in multi-radio wireless mesh networks." Ad Hoc Networks 10, no. 5 (2012): 760-773.

[2] Zhang, Degan, Mingjie Piao, Ting Zhang, Chen Chen, and Haoli Zhu. "New algorithm of multi-strategy channel allocation for edge computing." AEU-International Journal of Electronics and Communications 126 (2020): 153372.

[3] Gheisari, Soheila, and Mohammad Reza Meybodi. "LA-CWSN: A learning automata-based cognitive wireless sensor networks." Computer Communications 94 (2016): 46-56.

[4] Mogaibel, Hassen A., Mohamed Othman, Shamala Subramaniam, and Nor Asilah Wati Abdul Hamid. "Review of channel assignment approaches in multi-radio multi-channel wireless mesh network." Journal of Network and Computer Applications 72 (2016): 113-139.

[5] Khaksar Manshad, Mozhdeh, Mohammad Reza Meybodi, and Afshin Salajegheh. "A new multi-wave continuous action-set cellular learning automata for link prediction problem in weighted multi-layer social networks." The Journal of Supercomputing 78, no. 17 (2022): 18636-18665.

[6] Kim, Sok-Hyong, Dong-Wook Kim, and Young-Joo Suh. "A cooperative channel assignment protocol for multi-channel multi-rate wireless mesh networks." Ad Hoc Networks 9, no. 5 (2011): 893-910.

[7] Kumar, Neeraj, Manoj Kumar, and R. B. Patel. "Capacity and interference aware link scheduling with channel assignment in wireless mesh networks." Journal of Network and Computer Applications 34, no. 1 (2011): 30-38.

[8] Kumar, Neeraj, Sudip Misra, and Mohammad S. Obaidat. "Collaborative learning automata-based routing for rescue operations in dense urban regions using vehicular sensor networks." IEEE Systems Journal 9, no. 3 (2014): 1081-1090.

[9] Li, Fangmin, Yilin Fang, Fei Hu, and Xinhua Liu. "Load-aware multicast routing metrics in multi-radio multi-channel wireless mesh networks." Computer Networks 55, no. 9 (2011): 2150-2167.

[10] Marina, Mahesh K., Samir R. Das, and Anand Prabhu Subramanian. "A topology control approach for utilizing multiple channels in multi-radio wireless mesh networks." Computer networks 54, no. 2 (2010): 241-256.

[11] Nurlan, Zhanserik, Tamara Zhukabayeva Kokenovna, Mohamed Othman, and Aigul Adamova. "Resource allocation approach for optimal routing in IoT wireless mesh networks." IEEE Access 9 (2021): 153926-153942.

[12] Ramachandran, Krishna N., Elizabeth M. Belding-Royer, Kevin C. Almeroth, and Milind M. Buddhikot. "Interference-Aware Channel Assignment in Multi-Radio Wireless Mesh Networks." In Infocom, vol. 6, 2006, 1-12.

[13] Raniwala, Ashish, Kartik Gopalan, and Tzi-cker Chiueh. "Centralized channel assignment and routing algorithms for multi-channel wireless mesh networks." ACM SIGMOBILE Mobile Computing and Communications Review 8, no. 2 (2004): 50-65.

[14] Tian, Yi, and Takuya Yoshihiro. "Channel Assignment Based on CSMA-Aware Interference Model With Overlapped Channels in Multiradio Multichannel Wireless Mesh Networks." IEEE Access 10 (2022): 96695-96709.

[15] Beheshtifard, Ziaeddin, and Mohammad Reza Meybodi. "Maximal throughput scheduling based on the physical interference model using learning automata." Ad Hoc Networks 45 (2016): 65-79.

[16] Zlobinsky, Natasha. "Channel parameter tuning in a hybrid Wi-Fi-Dynamic Spectrum Access Wireless Mesh Network." (2023).

[17] Krishnammal, N., C. Kalaiarasan, and A. Bharathi. "Modelling a Learning-Based Dynamic Tree Routing Model for Wireless Mesh Access Networks." Computer Systems Science & Engineering 44, no. 2 (2023).

[18] Turlykozhayeva, D., N. Ussipov, A. Baigaliyeva, S. Temesheva, A. Bolysbay, G. Abrakhmatova, and S. Akhtanov. "Routing metric and protocol for wireless mesh network based on information entropy theory." Eurasian phys. tech. j 20, no. 46 (2023): 90-98.

[19] Ivanov, Valeriy, and Maxim Tereshonok. "Cross-Layer Methods for Ad Hoc Networks—Review and Classification." Future Internet 16, no. 1 (2024): 29.

[20] Khah, Mohammad Ali Mansouri, Neda Moghim, Nasrin Gholami, and Sachin Shetty. "Energy-efficient multi-rate opportunistic routing in wireless mesh networks." IEEE Access 11 (2023): 97466-97477.