Enhanced Clustering and Channel Allocation in Wireless Mesh Networks

Abstract. Wireless Mesh Networks (WMNs) are crucial for establishing adaptable and scalable communication infrastructures among interconnected devices. Effective clustering and channel allocation are vital for enhancing WMN performance by addressing energy efficiency, latency, throughput, and interference challenges. Proper clustering facilitates the organization of network nodes into cohesive groups, enhancing communication efficiency and resource utilization. Additionally, channel allocation strategies ensure minimized collisions and improved overall network throughput, enhancing network stability and reliability. Existing approaches, such as Clique-based Channel Assignment (CCCA) and Two-Hop Neighbor clustering, present complexity, and interference level limitations. The significant contribution of this paper is to introduce a novel approach focused on clustering and channel assignment, referred to as Enhanced Clustering and Channel Allocation (ECCA), to optimize WMN performance—the clustering technique groups nodes based on maximal cliques in one-hop neighbors. Furthermore, channel assignment strategies are employed to minimize collisions and improve overall network throughput. The performance of ECCA is compared with state-of-art Clique-based Channel assignment (CCCA) in terms of the modularity, average number of nodes per cluster, average node degree, and coefficient of variance.

Keywords: Wireless Mesh Networks · Clustering · Channel assignment.

1 Introduction

Wireless Mesh Networks (WMNs) are ad hoc networks where devices dynamically form temporary connections without relying on a central infrastructure [1, 2]. Nodes continuously monitor the quality of their links and adjust their communication accordingly to maintain optimal network performance. WMNs represent a vital component of modern communication infrastructures, characterized by their decentralized architecture and self-organizing and healing capabilities. Mesh clients, conversely, are end-user devices that connect to the network to access its services. Gateways act as intermediaries between the WMN and external networks, enabling connectivity to the internet or other external resources. Unlike traditional star topologies, where all nodes are connected to a central point, WMNs allow direct communication between neighboring nodes, offering resilience and flexibility in network design.

Clustering and channel allocation play crucial roles in WMNs, optimizing network performance and resource utilization. Clustering [3] enhances network organization, enabling efficient node management and reduced overhead, while channel allocation ensures effective spectrum utilization, minimizing interference and improving network reliability and throughput. However, WMNs face significant clustering and channel assignment challenges despite their advantages. The existing clustering techniques often rely on two-hop neighbor information to form clusters, resulting in suboptimal cluster formations [4, 5]. A two-hop neighbor refers to a node within the transmission range of its immediate neighbors but not in their transmission range. Additionally, the channel assignment strategies employed in WMNs may only partially eliminate interference, leading to reduced network performance. Interference can be broadly classified into coordinated and non-coordinated interference. Coordinated interference occurs when multiple nodes within each other's transmission range transmit data simultaneously, reducing network capacity and degrading performance. On the other hand, non-coordinated interference arises from nodes outside the immediate transmission range but still causes interference due to overlapping channels. Non-coordinated links lead to higher packet loss and uneven capacity distribution, causing more significant interference than coordinated links [5].

The algorithm Enhanced Clustering and Channel Allocation (ECCA) aims to improve the performance of WMNs by strategically organizing nodes into clusters based on maximal cliques among one-hop neighbors. One-hop neighbors are nodes directly within each other's transmission range without intermediate nodes. A maximal clique [6] is a subset of nodes in a graph where every node is directly connected to every other node in the subset. In the context of WMNs, a maximal clique represents a group of nodes that can communicate with each other directly. The channel allocation procedure is intended to allocate channels based on different interference levels to reduce interference. The cluster head coordinates data aggregation [7] using Carrier Sense Multiple Access Protocol (CSMA/CA) [8]. CSMA ensures that only one node transmits data at a time, reducing the likelihood of collisions and maximizing channel utilization. This approach is efficient when multiple nodes share the same communication medium.

The remaining paper is organized as follows: Section 2 introduces related works, the design, and implementation in Section 3, our results and analysis are presented in Section 4, and Section 5 concludes the paper.

2 Literature Survey

This section reviews the papers contributing to clustering and channel allocation in Wireless networking. S. Verma *et al.* [4] propose an energy-efficient clustering approach in WMNs using two-hop neighbors but overlooks different interference levels, potentially impacting network performance as discussed below in the subsection 2.1. Rong Dong *et al.* [5] propose a clique-based channel allocation scheme that considers different interference levels, as discussed below in the subsection 2.2. Priyadarshi *et al.* [9] propose a clustering and cluster head selection algorithm considering the residual energy of the nodes in the cluster as discussed below in Subsection 2.3.

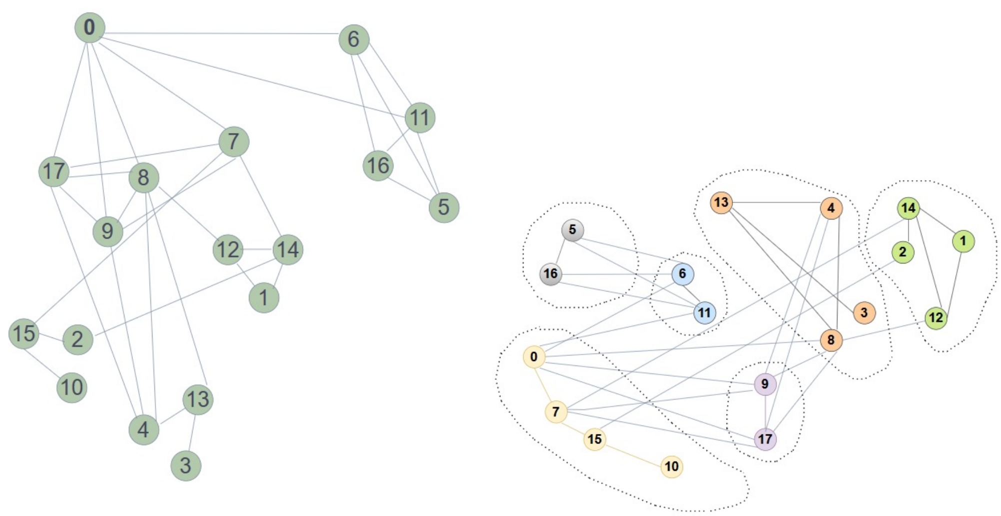
Guiqi Sun *et al.* [10] compare three popular classes of algorithms, namely distance-based (K-Power-Means), density-based (K-power-density), and evolution-based clustering methods for time-varying Multipath Components in Wireless Channels. However, it overlooks the different levels of interference involved. Subbaiah *et al.* [11] propose a Breadth First Search (BFS) approach to assign channels to the interfaces of multi-radio mesh routers, considering both coordinated and non-coordinated interference. Naveed *et al.* [12] proposed a channel allocation process that involves partitioning the WMN into clusters and employing a greedy approach to minimize both non-coordinated and coordinated interference by strategically assigning channels to each cluster's interfaces. Alishavandi *et al.* [13] propose a scheme that facilitates intra-cluster communication on a shared channel and employs orthogonal channels for inter-cluster communication, effectively reducing uncoordinated interference while addressing the challenge of coordinated interference within clusters.

2.1 Two Hop Neighbor clustering

Karthikeyan *et al.* [4] focused on efficient energy optimization in WMNs using cluster points. Here, the authors focus on clustering and cluster head selection in WMNs. They introduce a clustering approach for organizing two-hop neighbors into clusters, which can simplify channel assignment and resource allocation within the network. Further, they utilize the HEED cluster head selection algorithm [9], which considers node energy levels for cluster head selection, promoting energy efficiency.

However, despite the advancements in clustering techniques, the paper lacks consideration for the nuanced levels of interference that can arise from transmissions within the network, potentially impacting network performance. The focus on energy-efficient cluster head selection may overlook other important factors influencing network performance and robustness. Due to the consideration of two-hop neighbors, the number of connections within clusters is decreased.

2.2 Clique-Based Clustered Channel Assignment (CCCA)



((a)) Before clustering ((b)) After Clustering

Fig. 1: Clustering using CCCA

Syed *et al.* [5] discussed clustering and channel assignment in CCCA. The clustering is performed using maximal cliques within two-hop neighbors of each node. Firstly, the maximal cliques are identified within the two-hop neighborhood of each node. These cliques represent groups of nodes that are interconnected within a transmission range. After identifying these cliques, remove the nodes belonging to these cliques from the graph. Then, for the remaining nodes, recalculate the maximal cliques within their two-hop neighborhood. A node is added to neighboring clusters if it does not belong to any existing clique. However, if it forms a maximal clique with nodes in its two-hop neighborhood, it becomes the core of a new cluster. If any cluster size is smaller than two, they are added to the neighboring clusters. As the above discussion states, Fig. 1(b) depicts the clustering using CCCA of the topology represented in Fig. 1(a). The cliques in the graph represented in Fig. 1(a) are $\{0,7\}$, $\{5,16\}$, $\{9,17\}$, 4: $\{6,11\}$, $\{4,8\}$, $\{12,14\}$, based on the two-hop neighbours of the vertices. These vertices are removed from the graph, and the clusters are formed from the above cliques. Additionally, the other nodes that do not have two-hop neighbors are added to the clusters of their neighboring nodes. The clusters then formed are $\{0,7,10,15\}$, $\{1,2,12,14\}$,$\{3,4,8,13\}$, $\{5,16\}$, $\{6,11\}$, $\{9,17\}$.

It assigns default channels to clusters using the backtracking algorithm, ensuring nodes within clusters use coordinated channels for intra-cluster transmission. Inter-cluster links receive channels distinct from default channels to mitigate non-coordinated interference. It assigns channels for interfering links by considering neighboring link channel allocations to optimize inter-channel assignment within the network. This approach is complex because it identifies maximal cliques among the two-hop neighbors and forms clusters. Additionally, considering two-hop neighbors may decrease the number of connections within clusters, as some nodes may be excluded from clusters if they do not form maximal cliques. However, inter-cluster links may increase in number. Since each cluster has a designated cluster head responsible for inter-cluster communication, the number of inter-cluster links does not significantly impact network performance.

2.3 Hybrid Energy Efficient Distributed (HEED)

In the paper [9], the authors delve into the realm of Wireless Sensor Networks (WSNs) and focus on the crucial tasks of clustering and cluster head selection. Every node initially calculates its remaining energy and notifies its neighbors of it. Each node generates a random number influencing a node's decision to become a cluster head. The node's residual energy is used to calculate a threshold value and to compare it to this random number.

$$CH_{prob} = C_{prob} * \frac{E_{residual}}{E_{max}} \tag{1}$$

Eq. 1 represents the probability of a node becoming cluster head where C_{prob} is the Initial probability, $E_{residual}$ is the Residual energy, and E_{max} represents the Maximum energy of the nodes. Higher residual energy nodes are more likely to produce random numbers below the cutoff, increasing the likelihood that they may lead a cluster. On the other hand, nodes with lower energy levels are less likely to produce random numbers below the cutoff, which lessens the likelihood that they would lead a cluster. This probabilistic method considers the energy restrictions of individual nodes and guarantees a fair distribution of cluster heads throughout the network.

$$T\left(n\right) = \begin{cases} \frac{P}{1-P(r \ mod \ 1/P)} & if \ n \in G \\ 0 & otherwise \end{cases} \tag{2}$$

Eq. 2 represents the probability of a node becoming a cluster head using HEED where P represents the present round, r is the proportion of choosing Cluster Heads (CHs), and G denotes the group of all nodes that are not CHs in the 1/P rounds. In addition to overseeing intra-cluster communication, these cluster heads are in charge of data forwarding to the gateway and other cluster heads.

3 Design and Implementation of ECCA

This section presents a comprehensive overview of the proposed solution for addressing the challenges of clustering and channel assignment in WMNs. The proposed approach implements a static clustering and channel assignment scheme managed by a gateway. Subsection 3.1 briefs about the clustering algorithm used, Subsection 3.2 explains the channel allocation method, and Subsection 3.3 describes the performance metrics used to evaluate ECCA.

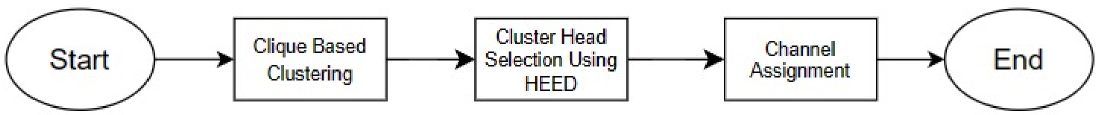


Fig. 2: Flow of implementation of ECCA.

Fig. 2 shows that the network is partitioned into clique-based clusters. The cluster head shall be selected depending on the energy remaining in nodes after clustering has taken place using HEED. Section 2.3 explains the algorithm in detail. Assign a channel between clusters for inter-cluster communication after assigning a default channel to each cluster for intra-cluster communication. Each cluster operates on a single channel, facilitating efficient node communication. The cluster head coordinates data aggregation, allowing time for potential data accumulation between transmissions using CSMA/CA [8]. Intermediate cluster heads can aid routing to distant receiver cluster heads, reducing energy consumption by minimizing direct long-distance communication.

3.1 Clique based Clustering:

A central gateway enables WMN [1] nodes to be connected to the Internet. To create a neighboring list and alert additional nodes to its presence, every node broadcasts hello packets at the start of each initialization. This list and the node ID are received by the gateway, which will build a network topology based on that connectivity information. This process enables nodes to set up communication channels with the gateway, thus making network management and data transfer more efficient.

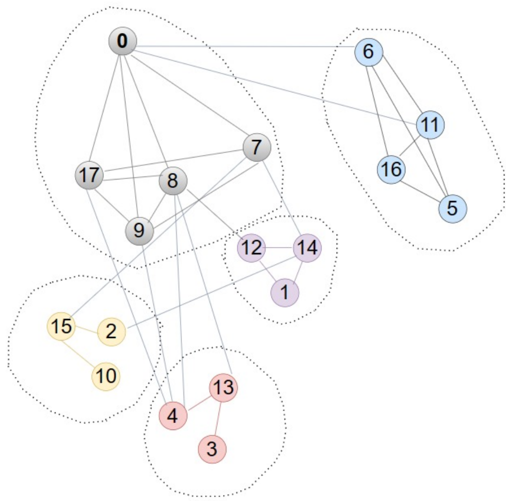


Fig. 3: Clustering using ECCA

The gateway transforms the graph into an interference graph, after which the gateway runs the clustering process. The clustering algorithm is explained with the example shown in Fig. 3. It depicts the clustering using ECCA for the example in Fig. 1(a). The solid nodes represent the mesh routers, and the line shows the link between them. A unique color is used to represent each cluster. Firstly, find the maximal clique from the interference graph and remove the vertices until no maximal clique of size 2 exists. Add the nodes not part of any cluster and the clusters smaller than or equal to 2 to a cluster with the minimum number of nodes among its neighboring clusters. Algorithm 1 represents the implementation of the clustering process, which is explained below using Fig. 3.

Algorithm 1 Cluster Formation

```
Initialize: Interference graph G and its copy G′.
Calculate all maximal cliques CL in G′.
while ∃CL_v ∈ CL with |CL_v| ≥ 2 do
    Form clusters from maximal cliques CL_v.
    Remove cliques CL_v from G.
    Remove vertices in CL_v from the graph copy G′.
end while
for each vertex v in V do
    Add the node to its neighboring node cluster.
end for
for each cluster do
    if size is less than or equal to 2 then
        Add nodes to the neighboring cluster.
    end if
end for
```

The maximal cliques among the one-hop neighbors in the graph represented in Fig. 1(a) are $\{0, 7, 9, 17\}$, $\{5, 6, 11, 16\}$, $\{12, 14\}$, $\{2, 15\}$, $\{4, 13\}$, these vertices are removed from the graph and the clusters are formed out of the above cliques (lines 2 - 7). Additionally, node 10, node 3, and node one are added to clusters containing nodes $\{2, 15\}$, $\{4, 13\}$ and $\{12, 14\}$ respectively as per the provided algorithm (lines 8 - 10). Then, check for the clusters whose size is less than or equal to 2; if present, add them to the neighboring clusters (lines 11 - 15). In the example Fig. 3, there exists no cluster with a size less than or equal to 2; hence, the final clusters remain the same and are depicted in Fig. 3.

3.2 Channel assignment

Algorithm 2 Channel Assignment

```
1: function ASSIGN_CHANNELS(clusters, graph)
2:     channel_counter ← 1
3:     for each cluster C_i do
4:         allocate default channel
5:         channel_counter ← channel_counter + 1
6:     end for
7:     for each cluster C_i do
8:         for each subsequent cluster C_j do
9:             inter_channel ← 1
10:            while true do
11:                if inter_channel is not equal to the default channels of clusters i and j and not previously
    used for inter-cluster communication then
12:                    break
13:                end if
14:                inter_channel ← inter_channel + 1
15:                if inter_channel > num_channels then
16:                    num_channels ← num_channels + 1
17:                end if
18:            end while
19:            assign this interchannel to both these clusters
20:        end for
21:    end for
22: end function
```

The inter-cluster communication leads to non-coordinated interference, and intra-cluster communication leads to coordinated interference. As the interference due to non-coordinated interference is greater than that of coordinated interference, reducing non-coordinated interference becomes the priority. It allocates channels as specified in Algorithm 2 to mitigate interference and optimize resource utilization. Subsection 3.2 and Subsection 3.2 explain the reduction of interference using Algorithm 2.

Intra-Cluster Channel Assignment: As shown in Algorithm 2, each cluster is assigned a unique default channel to facilitate communication among its constituent nodes (lines 3 - 6). This ensures that nodes within the same cluster can effectively exchange information without interference from nodes in other clusters. Minimizes the likelihood of collisions and packet loss within clusters, contributing to the overall robustness of the network. Reduces the complexity of routing protocols, as nodes within the cluster operate on the same channel.

Inter-Cluster Channel Assignment: Next, we assign channels for inter-cluster links to enable communication between clusters. This process ensures that inter-cluster channels are distinct from the default channels assigned to individual clusters. For each pair of clusters, search for a channel that is not the default channel of either cluster or used in previous inter-cluster channels (lines 10 - 18). Assign the channel for the inter-cluster communication which follows the above condition (line 19). To prevent channel duplication between clusters and maintain channel diversity, we utilize a comprehensive check to verify that the selected inter-channel has yet to be used within the network. This ensures inter-cluster communication occurs on distinct channels, minimizing interference and enhancing network reliability.

3.3 Performance Metrics

To comprehensively evaluate the effectiveness of our clustering algorithm, we delve into several performance metrics, each shedding light on different aspects of network organization and efficiency. In this section, we explore modularity, coefficient of variance, average nodes per cluster, average node degree, and their impact on clustering.

Modularity: Modularity [14], in the context of clustering algorithms, measures the quality of the resulting clusters. Modularity quantifies the quality of clusters by measuring the extent of intra-cluster connectivity relative to inter-cluster connectivity.

$$Q = \frac{1}{2m} \sum_{ij} \left(A_{ij} - \frac{k_i k_j}{2m} \right) \delta(C_i, C_j) \tag{3}$$

Eq. 3 is used to calculate the modularity of the clusters where, A_{ij} represents the adjacency matrix of the network, k_i and k_j denote the degrees of nodes i and j respectively, m is the total number of edges in the network, $\delta(C_i, C_j)$ is a delta function that equals 1 if nodes i and j are in the same cluster and 0 otherwise.

Average Nodes per Cluster: The average number of nodes [15] contained within each cluster in a network is calculated as shown in Eq. 4.

$$\text{AvgNodesPerCluster} = \frac{\sum_{i=1}^{N} |C_i|}{N} \tag{4}$$

where, N is the total number of clusters, $|C_i|$ represents the number of nodes in the i^{th} cluster.

The average number of nodes per cluster directly influences the size and structure of the clusters in a network. Higher averages lead to larger clusters, impacting scalability and resource allocation efficiency, while lower averages result in smaller, more localized clusters, potentially reducing contention and latency within the network. Striking a balance in this parameter is essential for optimizing network performance and resource utilization.

Coefficient of Variance: The coefficient of variance [16] assesses the uniformity of cluster sizes.

$$CV = \frac{\sigma}{\mu} \times 100\% \tag{5}$$

The coefficient of variance is calculated using the Eq. 5 where, σ represents the standard deviation of cluster sizes, μ denotes the mean cluster size.

The coefficient of variance in clustering quantifies the variation in cluster sizes within a network. A lower coefficient of variance indicates a more uniformly sized cluster, leading to a balanced resource distribution across the network. This balanced distribution enhances network stability by preventing specific cluster overload and ensuring efficient resource utilization. A lower coefficient of variance also promotes better load balancing and resilience to node failures, contributing to overall network efficiency and performance.

Average Degree Node: The average degree node [17] measures the average connectivity of nodes within clusters. It is determined by calculating the average degree of nodes in each cluster and adding all the obtained averages, where the degree of a node refers to the number of edges incident upon it. The higher average degree of nodes contributes to superior performance in forming clusters with more significant interconnections. So, it facilitates efficient communication and information exchange among cluster members. It allows for more direct and robust communication paths within clusters, enhancing network performance regarding data transmission, message routing, and overall network stability.

4 Results and Analysis

In this section, a series of simulations are conducted to evaluate the performance of the scheme ECCA using the programming language C++. WMN is simulated, which consists of n nodes, and an interference graph is used to represent it. Random positions are assigned to each node within the simulation space, with the number of nodes n varying. The simulation is conducted five times for each n, and the average is considered. The performance of ECCA is compared with state-of-art CCCA. In ECCA, nodes form clusters based on one-hop neighbor maximal clique information, emphasizing local connectivity. In CCCA, clusters are formed based on two-hop neighbors' maximal cliques.

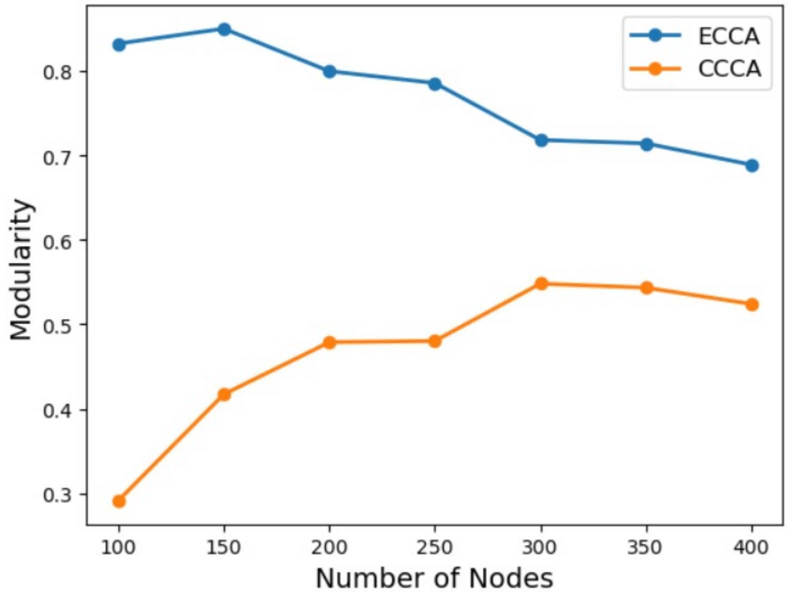


Fig. 4: Variation of modularity of clusters with number of nodes.

Fig. 4 depicts high modularity in ECCA, which can be attributed to its tendency to form clusters with more significant interconnections among their constituent nodes than CCCA.

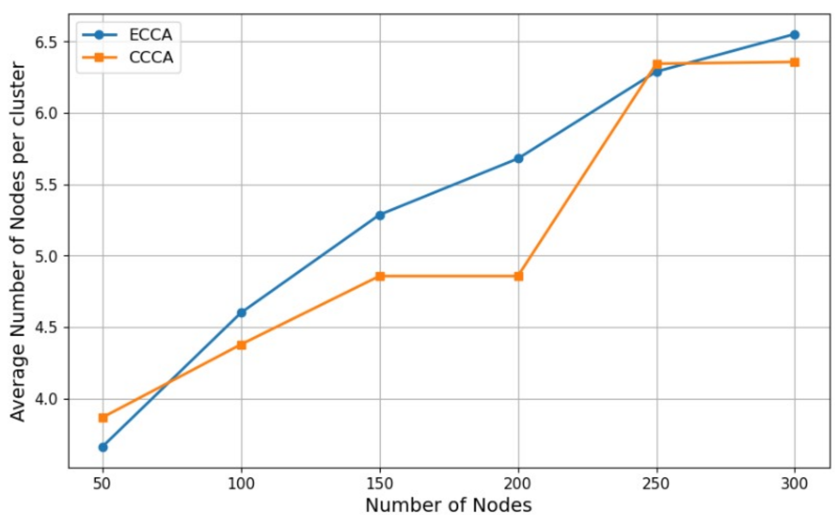


Fig. 5: Average number of nodes per cluster in ECCA and CCCA.

It is observed that ECCA tends to exhibit a slightly higher average number of nodes per cluster compared to CCCA, as depicted in Fig. 5. ECCA prioritizes the inclusion of neighboring nodes within a cluster, considering nodes within a one-hop neighborhood. Additionally, ECCA allows for the addition of smaller clusters to the clusters of their neighboring nodes. As a result, ECCA tends to form larger clusters than CCCA due to the aggregation of nodes from neighboring clusters.

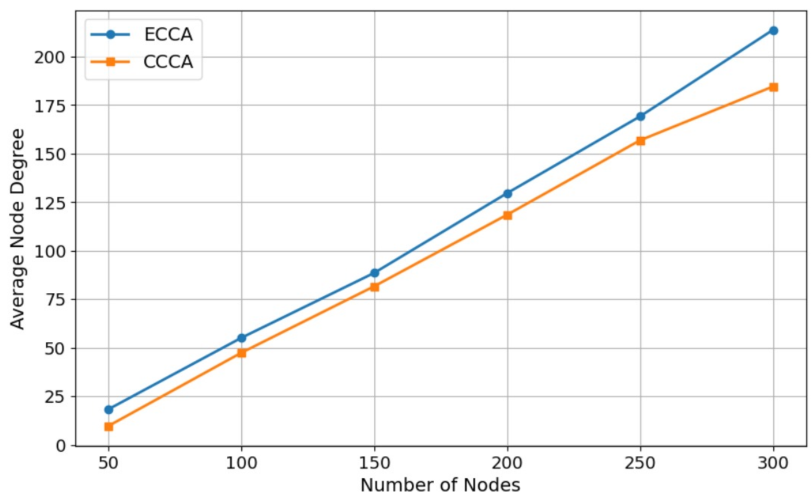


Fig. 6: Average node degree across the clusters.

Nodes within ECCA clusters tend to have a higher average degree than nodes in clusters formed by CCCA, as depicted in Fig. 6. This higher average degree implies that nodes in ECCA clusters are more densely connected to their neighbors within the same cluster.

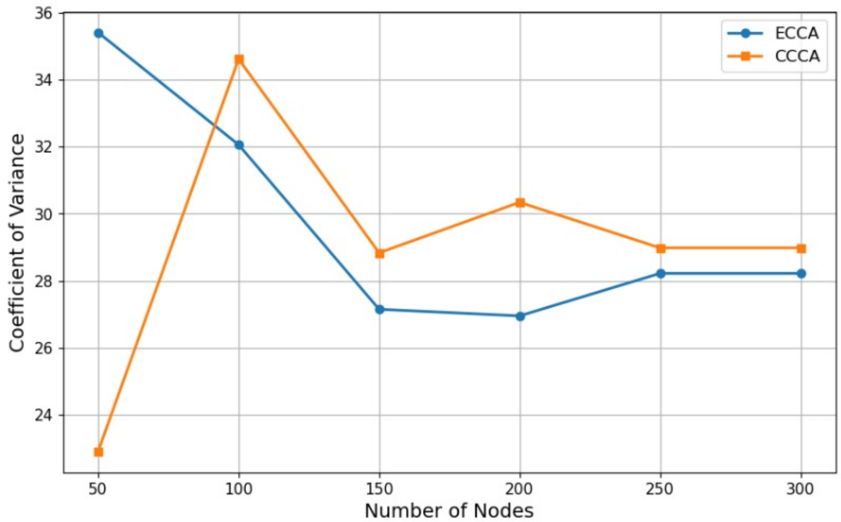


Fig. 7: Coefficient of variance for varying number of nodes.

As depicted in Fig. 7, ECCA exhibits lower variance in cluster sizes than the CCCA, indicating a higher level of uniformity. Specifically, ECCA demonstrates a narrower distribution of cluster sizes, resulting in more homogeneous clusters regarding node count.

5 Conclusion and Future Work

This paper introduces an algorithm aimed at enhancing the performance of WMNs through efficient clustering and channel assignment, considering various levels of interference. A significant discovery from the study is the advantage of one-hop clique-based clustering over two-hop clique approaches, notably in enhancing the quality of clustering and simplifying the computation process by eliminating the need to calculate two-hop neighbors while considering interference levels. Leveraging maximal cliques among one-hop neighbors, the ECCA algorithm effectively reduces complexity and optimizes the formation of clusters. Future research directions may include further optimization of algorithm parameters, evaluating scalability in larger network deployments, exploring dynamic clustering techniques, and assessing the applicability of the proposed algorithm in other simulation environments like NS2 or NS3.

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