Distributed Channel Assignment to Mitigate Co-Channel Interference in Ultra-Dense Wireless Networks

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Abstract

In ultra-dense wireless networks (UDNs), co-channel interference poses a significant challenge to maintaining network performance and reliability. The presence of co-channel interference can degrade the signal quality for legitimate users and can create vulnerabilities in the overall network structure making it susceptible to Denial of Service and Jamming Attacks.

A common strategy to mitigate this interference is to assign orthogonal channels to wireless devices, but computing an optimal channel assignment is an NP-hard problem, involving high computational complexity. In this paper, we present a distributed channel assignment algorithm that offers a scalable solution to mitigate such interference. Our analysis shows that the the resulting interference from our algorithm is near optimal and, in the worst case, that the resulting interference that is no more than twice offered by the optimal solution.

Keywords: Distributed Channel Assignment, Co-Channel Interference, Ultra-Dense Networks, Online Edge Coloring, Security in Wireless Networks.

1. INTRODUCTION

The proliferation of wireless devices and the Internet of Things (IoT) has led to an unprecedented surge in network density, giving rise to the concept of ultra-dense networks (UDNs). These networks are characterized by a high concentration of low mobility wireless nodes, a wide variety of access points, and user equipment within confined areas, significantly increasing the complexity of network management (Chen, 2016). This explosive growth is fueled by advancements in 5G technology, edge computing, and the widespread adoption of smart devices across sectors such as healthcare, manufacturing, and smart cities. The global IoT market has reached 14.7 billion in 2023, highlighting the rapid expansion of connected devices (Adedoyin, 2020; Cisco, 2020; Dewa, 2021).

This density increase results in significant co-channel interference (CCI), posing a major challenge in wireless networks that can affect both the reliability and security of communications. CCI has a significant impact on the security-reliability trade-off in wireless networks. The presence of CCI can degrade the signal quality for legitimate users: CCI decreases the Signal-to-Interference-plus-Noise Ratio (SINR), making it harder for legitimate receivers to accurately decode transmitted messages. The degraded signal quality leads to a higher BER, potentially compromising the integrity of transmitted data (Li, 2021).

In addition, CCI can create vulnerabilities in the overall network structure making it susceptible to Denial of Service (DoS) and Jamming Attacks where adversaries exploit interference to degrade network performance (Li, 2019).

In light of these challenges, reducing CCI is crucial to improve most network performance factors, such as the overall throughput, latency, and control overhead in ultra-dense wireless networks. The current IEEE 802.11 Wireless-Fidelity (Wi-Fi) and its derivatives (e.g., 802.11n, 802.11ac, 802.11ax, 802.11be) allows the use of multiple orthogonal 20 MHz channels. One way to reduce co-channel interference is to assign orthogonal channels to network nodes that are in close proximity to each other (Alicherry, 2005; Katzela, 1996; Raniwala, 2005). However, the large number of wireless nodes in ultra-dense wireless networks considerably outnumbers the available channels. Determining the optimal channel for each wireless node is an NP-Hard problem that requires a very high computational complexity.

There is a substantial body of work on the channel assignment problem. In Section 2, we provide a background and a review of existing approaches to mitigate co-channel interference (CCI) in wireless networks, including centralized, distributed, heuristic, and machine learning-based approaches. In Section 3, we introduce our systems and threat model. We propose a distributed channel assignment algorithm in Section 4. Our algorithm differs from existing literature by offering a provable performance guarantee on the amount of interference, ensuring that it remains within a bounded gap from the optimal solution.

2. LITERATURE REVIEW

Channel assignment to reduce CCI has been studied by many researchers. As the problem is NP-hard, the complexity of finding an optimal assignment is computationally infeasible in a network with an increasing number of devices. As a result, many approaches focused on designing sub-optimal but efficient algorithms.

1. Static Channel Assignment

In static channel assignment, it is assumed that the nodes and communication links are given as an input and are stationary and are known a priori. While static assignments can be useful in predictable environments, they fail to adapt to network changes, making them less effective in dynamic settings such as ultra-dense wireless networks. Static methods are suitable for environments with minimal device mobility and minimal network changes. Algorithms to solve channel assignment can becategorized into centralized and distributed algorithms.

1.1. Centralized Channel Assignment

In centralized channel assignment algorithms, a central server collects channel and link information from all network nodes. This aggregated information is then utilized by the algorithm, to determine the channel assignment for each link in the wireless network. The results are then communicated back to the network nodes, which configure their interfaces accordingly (Drieberg,2012; Sarasvathi, 2012). Approaches in this setting include a probabilistic greedy algorithm (Amiri, 2010), genetic algorithms (Al-Habob, 2020; Han, 2010) and particle swarm optimization (Peras, 2020; Xing, 2019).

1.2. Distributed Channel Assignment

In distributed channel assignment algorithms, each node independently determines the appropriate channels for its links based on locally available information. This has the advantage of reducing traffic overhead and avoids centralized bottlenecks, making it more suitable for UDNs (Alicherry, 2005; Kyasanur, 2005, Raniwala, 2005, Shin, 2006).

2. Dynamic Channel Assignment

Static channel assignment approaches cannot efficiently adapt to dynamically changing networks. In this paper we consider dynamic wireless networks where nodes and communication links arrive online and change over time. This requires real-time or periodic reassignment of channels to maintain network performance.

2.1. Interference or Conflict Graphs

Network nodes that interfere with each other are connected by edges in a conflict graph, typically based on a determined signal-to-interference-noise (SINR) threshold. Recent approaches introduced graph-based algorithms to solve the channel assignment problem by minimizing the number of conflicts in the graph (Zhao, 2015). A centralized efficient genetic algorithm was introduced for mobile networks (Al-Habob, 2020), while graph coloring algorithms were presented as a solution to minimize CCI (Kari, 2014; Zhao, 2018).

2.2. Other Approaches for Dynamic Channel Assignment

For mobile networks a deep reinforcement learning framework was introduced and looks at a solution where Non-orthogonal multiple access is used for wireless communication (He, 2019). A distributed algorithm that uses a message passing framework and belief propagation was introduced for dynamic networks (Dewa, 2021). The solution proposed finds an optimal assignment. However it does not scale well with an increasing number of devices in the system.

In this paper, we present an efficient distributed greedy algorithm for dynamic UDNs. Our graph coloring algorithm differs from the approaches above as to provides a worst-case guarantee that the number of conflicts resulting from the channel assignment is no more than twice that of the optimal solution.

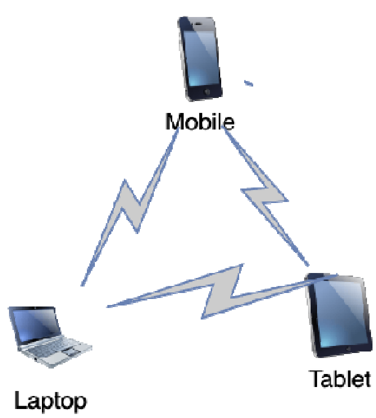
3. MODEL AND PROBLEM DEFINITION

We model the channel assignment problem to reduce CCI with a conflict or interference graph. The graph is defined as follows:

3.1. Conflict Graph

We are given a $G = (V, E)$ representing a wireless network. Nodes in the graph represent devices in the network. An edge $e = (u, v) \in E$ represents a communication link between the nodes $u, v \in V$ if the nodes interfere with each other i.e. if a determined signal-to-interference-noise (SINR) threshold is exceeded.

Consider the following simple wireless network represented by the corresponding conflict graph shown in following figure.



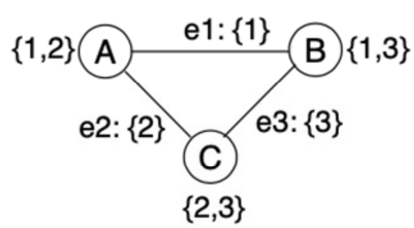


FIGURE1: Each node has can use two different channels. We can assign a distinct channel to each link as shown above so that there is no interference among links.

If links e_1, e_2 and e_3 all use the same channel for transmission, only one pair of nodes can communicate without interference at any given time. This scenario is unrealistic, as we typically expect all links to transmit simultaneously. However, if each device has access to three different channels, we could assign a unique channel to each link, allowing all links to operate without interference. For example, we could assign channel 1 to e_1, channel 2 to e_2 and channel 3 to e_3.

In our model, we use edge coloring of the conflict graph to represent channel assignment, and we represent the various channels by colors in the remainder of the paper. For example, in Figure 1 above, we can assign color red to e_1, green to e_2 and blue to e_3.

Unfortunately, in UDNs, the number of communication links far exceeds the number of available channels, making interference unavoidable. The goal, therefore, is to assign channels to communication links in a way that minimizes interference.

3.2. Counting Conflicts

Each node v has a constraint c_v that represents the number of different channels available at $v$and the total number of channels that can be used in the network is represented by C_G.

Let $E(v)$ be the set of edges incident to v and $c(e)$ be the channel assigned to e.

$$\text{Then} \left|\bigcup_{e \in E(v)} \{c(e)\}\right| \leq c_v \text{ and } \left|\bigcup_{e \in E} \{c(e)\}\right| \leq C_G.$$

A pair of edges $e_1, e_2 \in E(v)$ are said to be conflicting if they are assigned the same channel. We define the *conflict number*, $CF_e(v)$ of an edge $e \in E(v)$ to be the number of edges that are incident to v and conflict with e (including e itself).

Our goal is to minimize the total number of conflicts in the conflict graph:

$$CF_G = \sum_{e=(u,v) \in E} \left(CF_e(u) + CF_e(v)\right). \quad (1)$$

Note that in equation (1) each conflict is counted twice in CF_G. An equivalent definition would be to define CF_G as the sum of the squares of the color classes at each node. Let $E_i(v)$ be the set of edges with color i at node v.

Then we can define CF_G as follows:

$$CF_G = \sum_{v \in V} \sum_i |E_i(v)|^2.$$

Note that $\sum_i |E_i(v)|^2$ is minimized locally at node v when edges in $E(v)$ are distributed evenly to each color i.

The following figure (Figure 2) shows an example of conflict graph with a complete assignment and the number of conflicts at each node and CF_G

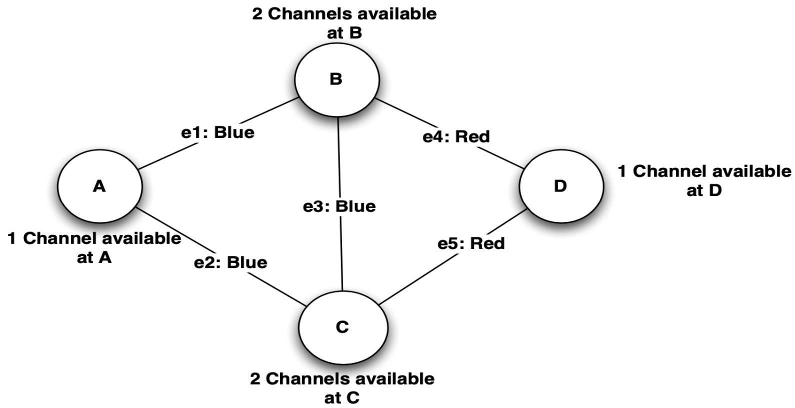


FIGURE 2:
$CF(e_1) = 4$ (2 conflicts at A and 2 conflicts at B),
$CF(e_4) = 3$(1 conflict at B and 2 conflicts at D),
$CF(e_2) = CF(e_3) = 4, CF(e_5) = 3.$

3.3. Threat Model

Various threat and adversary models have been studied in the context of wireless networks and channel assignment. Most threat models involve an adversary that can jam channels by transmitting random signals. These include adversaries that send signals continuously, randomly, or adaptively based on observed communication patterns (Grover, 2014).

In this paper, we consider a powerful adversary model—one that can control the arrival of new devices to the network, determine the location of these devices, and their proximity to other devices. In other words, this adversary can control the structure of the conflict graph.

3.4. Measuring Performance of Algorithms

Since the adversary controls the arrival rate and location of the nodes in the conflict graph, we propose a distributed online algorithm in which each node greedily selects its own channel for communication. To evaluate the performance of our algorithm, we use the competitive ratio, a standard metric for assessing the quality of online algorithms (Karlin, 1988; Sleator, 1985).

The competitive ratio of an online algorithm is the worst-case ratio, over all possible input sequences, of the number of conflicts generated by the online algorithm compared to the number of conflicts produced by the optimal offline algorithm.

More formally, for any online algorithm $\mathcal{A}$ and any sequence S of edges, let $CF_{\mathcal{A}(S)}$ be the number of conflicts produced by $\mathcal{A}$and let $CF_{OPT(S)}$ be the number of conflicts produced by the optimal offline algorithm. An online algorithm $\mathcal{A}$ is α −competitive if $CF_{\mathcal{A}(S)} \geq \alpha \cdot CF_{OPT(S)}$ for any sequence S of edges.

The competitive ratio of $\mathcal{A}$ is $\min_{\alpha}\{\mathcal{A} is \alpha - competitive\}$.

4. DISTRIBUTED ONLINE GREEDY ALGORITHM

4.1. NP-Hardness

We consider networks where all devices in the networks can use the same number of channels i.e. for any node $v \in G, c_v = k$ where k is the number of channels (or colors) available in the network.For an arbitrary $k > 2$, the problem is NP-hard as the edge coloring problem can be reduced to our problem by setting $k = C_G = \Delta$ where Δ is the maximum degree of nodes.

4.2. Online Greedy Edge Coloring Algorithm

We present and analyze the following distributed online greedy algorithm.

Let $n(c,e)$ denote the number of edges adjacent to e the are assigned color c. A sequence S of edges arrives online. For each uncolored edge e the algorithm greedily chooses the color for edge e that introduces the smallest number of conflicts or the lowest $n(c,e) for c \in \{1, \ldots, k\}$.

```
for each edge e ∈ S do
  for each color i do
    compute the number of edges in E(u) and E(v) using
    color i.
  end for
  let c be the color with min n(i, e) for all colors i.
  assign color c to edge e.
end for
```

Online Greedy Edge Coloring Algorithm

Note that the above algorithm is distributed as each node needs only local information to assign a color to an incoming adjacent edge.

We now show that the algorithm's competitive ratio is $(2 - \frac{1}{k})$.

4.3. Analysis

We now show lower bounds for the channel assignment problem and an upper bound for our algorithm.

Lemma 1a: The total number of conflicts for any algorithm and any sequence of S edges is at least:

$$CF_{OPT(S)} \geq \sum_v \frac{d_v^2}{k}.$$

Proof:

$$CF_G = \sum_{e=(u,v)} (|E_{c(e)}(v)| + |E_{c(e)}(u)|) = \sum_v \sum_{e \in E(v)} (|E_{c(e)}(v)|) = \sum_v \sum_i |E_i(v)|^2$$

For each node v, $\sum_i |E_i(v)|^2$is minimized when the size of $E_i(v)$ is the same for each color$i$. Since we have have$k$ colors:

$$CF_G \geq \sum_v \left(\frac{d_v}{k}\right)^2 \cdot k = \sum_v \frac{d_v^2}{k} \blacksquare$$

Lemma 1b: The total number of conflicts for any algorithm and any sequence of S edges is at least: $CF_{OPT(S)} \geq 2|E|$

Proof:
If no adjacent edges are assigned the same color, there are $2|E|$ conflicts in the graph as every edge contributes exactly one conflict at each endpoint.■

Lemma 2: *Upper Bound.* The total number of conflicts for our algorithm for any sequence of S edges is at most:

$$CF_G \leq \sum_v \frac{d_v^2}{k} + 2(1 - \frac{1}{k})|E|.$$

Proof:
Consider an edge $e = (u, v) \in G$. Let $n(e)$ be the number of conflicts that e introduces when it gets assigned a color. The total number of conflicts in the the graph is:

$$CF_G = \sum_e n(e).$$

Since the algorithm greedily chooses a color c for e such that it introduces the smallest number of conflicts in nodes u and v, there are at most $\lfloor\frac{d_v(e)+d_u(e)}{k}\rfloor$edges at u and v that have the same color as c where $d_u(e)$ and $d_v(e)$ represent the number of edges that get assigned a color before e in $E(v)$ and $E(u)$ respectively.

Therefore:

$$n(e) \leq 2\lfloor\frac{d_v(e)+d_u(e)}{k}\rfloor + 2$$

The additive term 2 is because e is counted as a conflict at both u and v. The total number of conflicts is:

$$\begin{aligned}
&CF_G = \sum_e n(e) \\
&\leq \sum_{e=(u,v)} (2\lfloor\frac{d_v(e) + d_u(e)}{k}\rfloor + 2) \\
&\leq 2\sum_v \sum_{e\in E(v)} \frac{d_v(e)}{k} + 2|E| = \frac{2}{k}\sum_v \sum_{i=0}^{d_v-1} i + 2|E| \\
&= \frac{2}{k}\sum_v \frac{d_v^2}{2} - \frac{2}{k}\sum_v \frac{d_v}{2} + 2|E| \\
&= \sum_v \frac{d_v^2}{k} + 2(1 - \frac{1}{k})|E| \blacksquare
\end{aligned}$$

We are now ready to show the following Theorem:

Theorem.The competitive ratio of the online greedy edge coloring algorithm is$(2 - \frac{1}{k})$.

Proof:
The competitive ratio of our algorithm is:

$$\frac{CF_G}{OPT} = \frac{\sum_{e \in E} CF_e}{OPT}$$

$$\leq \frac{\sum_v \frac{d_v^2}{k} + 2(1-\frac{1}{k})|E|}{OPT} \quad \text{(From Lemma 2)}$$

$$\leq \frac{\sum_v \frac{d_v^2}{k}}{\sum_v \frac{d_v^2}{k}} + \frac{2(1-\frac{1}{k})|E|}{2|E|} \text{(From Lemma 1a and 1b)}$$

$$= 2 - \frac{1}{k} \blacksquare$$

5. DISCUSSION AND CONCLUSION

In this paper, we studied the problem of distributed channel assignment in dynamic wireless networks, specifically focusing on reducing co-channel interference in ultra-dense environments. We proposed an efficient distributed greedy edge coloring algorithm that can adapt to network changes and provides a worst-case guarantee that the number of conflicts resulting from the channel assignment is no more than $2 - \frac{1}{k}$ that of the optimal solution where k is the number of channels available in the network.

Future work could explore our algorithm under different threat models, such as an adversary capable of disrupting communication links or jamming signals, as opposed to controlling the structure of the conflict graph. One promising direction is to incorporate machine learning techniques, such as reinforcement learning, to enable nodes to adapt their channel assignments based on evolving network conditions. Another area for future exploration would be to explore other practical issues that arise in UDNs such as signaling overhead and latency, among others.

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