Journal of Modern Researches on Electronic Defense Systems

Receive: 11 June 2024 Accept: 20 June 2024

Optimal and Suboptimal Algorithms for Resource Allocation in Dense Wireless Cooperative Networks

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Abstract – *Cooperative Networks are novel technologies for improving wireless system performance; therefore, they are a good candidate for future cellular networks. In these networks, nodes cooperate with their data and information to each other to increase the network's performance. Cooperative Networks have different architectures. Hundreds of wireless systems are located in a small area in some architecture. These architectures are named dense cooperative networks. Resource allocation can improve the performance of dense cooperative networks. Optimal resource allocation is a strategy for improving system performance and guaranteeing quality of service; hence, in this paper, we attempt to calculate optimal transmit power for nodes to achieve maximum allowable capacity by applying the convex optimization method. Convex optimization is a powerful tool for resource allocation and signal processing in wireless networks. In addition, due to the Complexity of the optimal solution, we introduce a novel suboptimal power allocation algorithm. Simulation results indicate that our proposed method can improve the performance of cellular networks.*

Keywords: Dense Wireless Cooperative Networks, Power allocation, convex optimization, optimal and suboptimal algorithms.

1. Introduction

Novel wireless communication technologies have been introduced in recent years to improve the performance of wireless communication systems. These technologies aim to improve mobile traffic data [1-3]. Cooperative communication is a novel technology technology that increases the throughput of systems. In cooperative networks, nodes can collaborate in information transmission [4-6]. Many nodes are located in the small area in the dense cooperative networks. Dense wireless cooperative networks have been proposed for next-generation wireless networks, e.g., Cloud-RAN. Cloud-RAN is a proposed architecture for future cellular networks supporting large-scale cooperative transceivers [7-9]. Usually, dense cooperative networks need to simultaneously manage hundreds of radio access units (RAUs) and mobile units (M.U.s). Therefore, resource allocation and signal processing problems are dramatically complex and complicated. Hence, several methods have been used to improve the performance of dense cooperative networks by allocating optimal resources to nodes. Indeed, these methods calculate nodes' resources, such as transmit power [10-12]. In some papers [13-16], the convex optimization method allocates optimal resource allocation. Convex relaxation can solve non-convex or NP-hard problems such as robust beamforming [17, 18]. In some research, such as [19, 20], authors introduced a new variable for each sub-expression in disciplined convex programming. Several algorithms are used for solving convex optimization [21-23]. Also, in [24], the CVX tool, [25] Lagrange method, and the [26] alternating direction method of multipliers (ADMM) algorithm are used for solving convex problems. Although an optimal procedure gives the system the best performance because of its Complexity, in some papers, suboptimal methods are used instead of optimal solutions. For instance, in [27], researchers introduced a suboptimal algorithm for power allocation in their proposed system. In this paper, we attempt to calculate the transmit power of nodes in dense cooperative networks. The purpose of power allocation is to guarantee system performance in all situations [28]. The proposed model is developed based on the Cloud-RAN; hence, it can be used in future cellular networks. Many M.U.s and RAUs are located in small areas in the proposed model. Therefore, it is necessary to handle interference introduced on nodes to guarantee quality of service (QoS). To improve the network's performance, M.U.s share their information; hence, user data and channel state information are available at the baseband unit (BBU) pool. BBU pool is the highest level in the Cloud-RAN network and processes signals in the baseband. This research aims to optimize the system's transmit power so that nodes have a maximum allowable transmission rate in all situations. The proposed method changes channel capacity based on the channel states. A convex optimization method is used to calculate the optimal solution. Due to the Complexity of the optimal solution, we introduce a novel suboptimal algorithm for power allocation in the proposed network model.

The rest of this paper is organized as follows: Section two describes the system model. In section 3, optimal and suboptimal solutions are described. Simulation results and conclusions are explained in sections 4 and 5, respectively.

2. Network Model

Figure 1 shows the architecture of Cloud-RAN. This model is similar to the one introduced in [29]. This network includes a BBU pool, RAUs, and M.U.s. M.U.s are connected to the BBU pool via RAUs. We assume user data and channel state information are available in the BBU pool; therefore, full cooperation between nodes is provided. In the proposed model, M.U.s can communicate to the BBU tool via different RAUs.

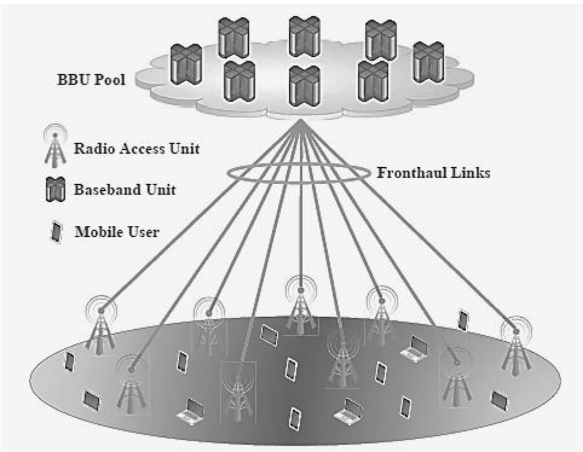

Figure 1. Proposed network model

Assume there are M RAUs and N single-antenna M.U.s in the proposed network. Channel gain between kth M.U. and mth RAU is indicated by h_{km}. Each M.U. receives data from all RAUs. Also, M.U. signals interfere with each other. Therefore, the received signal at kth M.U. can be expressed as follows [30]:

$$y_k = \sum_{m=1}^{M} h_{km}^T p_{mk} + \sum_{i \neq k} \sum_{m=1}^{M} h_{km}^T p_{mi} + n_k , \quad \forall k \tag{1}$$

Where p_{mk} indicates transmit power, n_k indicates Additive white Gaussian noise (AWGN) at the receiver with zero mean and σ^2 variance, and $(.)^T$ shows conjugate transpose. Equation 1 indicates that receivers in the dense cooperative networks are subjected to many interfaces. Based on the above Equation, signal-to-interface and noise ratio (SINR) can be calculated as follows:

$$SINR = \frac{\sum_{m=1}^{M} \left(h_{mk} p_m \right)}{\sum_{i \neq k} \sum_{m=1}^{M} \left(\left(h_{mk} p_i \right) + \sigma^2 \right)} \tag{2}$$

Channel capacity between kth M.U. and mth RAU can be obtained by the Shannon capacity formula as follows:

$$C = \log_2 (1 + SINR) \tag{3}$$

The Shannon capacity formula indicates that more SINR obtains more channel capacity. Hence, we need to increase SINR in the system by managing the transmit power of M.U.s. Higher transmit power results in higher channel gain. However, in the cooperative network, more allocated power introduces more interfaces on the other M.U. systems, decreasing the overall system's performance. Hence, it is necessary to calculate optimal transmit power so that all M.U.s in the network perform best. Calculating the optimal power allocation algorithm is too tricky, and it may need to be more useful in practical terms. Although, in some papers, researchers attempted to calculate optimal transmit power, our goal in this research is to find a simple and practical solution for the power allocation algorithm. We know transmit power is limited due to several factors. For example, maximum transmit power is restricted to guarantee QoS and prevent harmful interface production on the other M.U.s in the network. To achieve this purpose, the optimization problem is expressed as follows:

$$\max \ \log_2 \left(1 + \frac{\sum_{m=1}^{M} \left(h_{mk} p_m \right)}{\sum_{i \neq k} \sum_{m=1}^{M} \left(\left(h_{mk} p_i \right) + \sigma^2 \right)} \right) \tag{4}$$

Subject to:

$$\sum_{m=1}^{M} p_m \leq p_{\max} \tag{5}$$

$$p_m \geq 0 \qquad m = 1, ..., M \tag{6}$$

This optimization problem is convex. As mentioned before, several methods have been established for solving convex optimization. We use the Lagrange method to solve this problem and explain it in the next section.

3. Optimal and Suboptimal solutions

In the following, the necessary explanations regarding Optimal and Suboptimal. Solutions will be provided.

3.1. Optimal solution

In this section, we apply the Lagrange method to solve convex optimization, as expressed in the previous section. By applying the Lagrange method, we have:

$$L = \log_2\left(1+\frac{\sum_{m=1}^{M}\left(h_{mk}p_m\right)}{\sum_{m=1}^{M}\sum_{i\neq k}\left(\left(h_{mk}p_{mi}\right)+\sigma^2\right)}\right)+\alpha p_{mk}-\beta_m\left(\sum_{m=1}^{M}p_m-p_{\max}\right) \qquad (7)$$

Where α and β are Lagrange parameters and are non-negative values. Solving Equation 7 by calculating its derivative:

$$\frac{\partial L}{\partial p_{mk}}=0\Rightarrow\frac{1}{p_{mk}+\frac{\sum_{m=1}^{M}\sum_{i\neq k}\left(\left(h_{mk}p_{mi}\right)+\sigma^2\right)}{h_{mk}}}+\alpha-\beta_m=0 \qquad (8)$$

By applying Lagrange conditions, we have:

$$\alpha p_{mk}=0 \qquad \forall m\in M \qquad (9)$$

$$\beta\left(\sum_{m=1}^{M}p_m-p_{\max}\right)=0 \qquad \forall m\in M \qquad (10)$$

By removing α in Equation 7, we can calculate the following Equation:

$$\frac{1}{p_{mk}+\frac{\sum_{m=1}^{M}\sum_{i\neq k}\left(\left(h_{mk}p_{mi}\right)+\sigma^2\right)}{h_{mk}}}\leq\beta_m \qquad (11)$$

By multiplying p_{mk} in the Equation 11, Equation 12 can be obtained as follows:

$$\frac{p_{mk}}{p_{mk}+\frac{\sum_{m=1}^{M}\sum_{i\neq k}\left(\left(h_{mk}p_{mi}\right)+\sigma^2\right)}{h_{mk}}}-\beta_m p_{mk}=0 \qquad (12)$$

Therefore, we can calculate transmit power as follows:

$$p_{mk}=\frac{1}{\beta}-\frac{\sum_{m=1}^{M}\sum_{i\neq k}\left(\left(h_{mk}p_{mi}\right)+\sigma^2\right)}{h_{mk}} \qquad (13)$$

Transmit power cannot be negative. Therefore, optimal transmit power for k^{th} M.U. to transmit data to m^{th} RAU can be obtained by the following Equation:

$$p_{mk}=\max\left\{0,\frac{1}{\beta_m}-\frac{\sum_{m=1}^{M}\sum_{i\neq k}\left(\left(h_{mk}p_{mi}\right)+\sigma^2\right)}{h_{mk}}\right\} \qquad (14)$$

3.2. Suboptimal algorithm

The transmitter must substitute Equation 14 into Equation 5 to calculate optimal transmit power. Therefore, the optimal solution may only be appropriate for some practical applications. In this section, we introduce a novel suboptimal algorithm. We know modern M.U. systems have noise estimation units for estimating noise at the receiver. This unit does not distinguish between noise and interference. Therefore, we assume the value of noise and interference at the M.U.'s receiver is shown by φ. In addition, Equation 14 indicates that transmit power is proportional to channel gain. In other words, more power is allocated to M.U. with better channel gain and less to M.U. with worse channels. On the other hand, this Equation shows that transmit power is inversely proportional to the amount of noise and interference. Indeed, more power is allocated to a channel subjected to less noise and interference and vice versa. Therefore, we can have:

$$p_{mk}\propto\frac{h_{mk}}{\varphi} \qquad (15)$$

Equation 15 can be rewritten as an equal expression by the following Equation:

$$p_{mk}=Q\times\frac{h_{mk}}{\varphi} \qquad (16)$$

Where Q is a constant value, we substitute Equation 16 into Equation 5 for calculating Q and assume it as an equality Equation. Therefore, the value of the Q is obtained as follows:

$$Q=\frac{\varphi\times p_{\max}}{\sum_{m=1}^{M}h_{mk}} \qquad (17)$$

Therefore, transmit power based on our proposed suboptimal algorithm can be calculated as follows:

$$p_{mk}=\frac{h_{mk}\times p_{\max}}{\sum_{m=1}^{M}h_{mk}} \qquad (18)$$

4. simulation results

In this section, we evaluate the proposed model by using numerical examples. We assume channels between M.U.s and RAUs have Rayleigh distribution with unit mean. In addition, there are 10 RAUs and 64 M.U.s in the network. Noise at receiver has Gaussian PDF with zero mean and 10^{-6} watt variance. The bandwidth of each M.U. is assumed to be 1 MHz. Also, we assume the maximum overall power allocated to M.U.s is 10 dB. In this section, the performance of the optimal solution is compared with suboptimal and uniform loading solutions. In the uniform loading solution, equal power is allocated to all M.U.s. The uniform loading algorithm has been used in many practical networks. As mentioned before, each M.U. communicates with all RAUs. We aim to calculate the transmit power between each M.U. and all ARUs. Figure 2 shows the transmit power for all 10 ARUs to transmit data to specific M.U. In other words, for each M.U., we should calculate the transmission rate for ten links. This figure shows that equal power is allocated to each link using a uniform loading algorithm, while for optimal and suboptimal solutions, different power is allocated to links. In addition, this figure indicates that using the optimal procedure, more power can be allocated to links rather than the suboptimal algorithm.

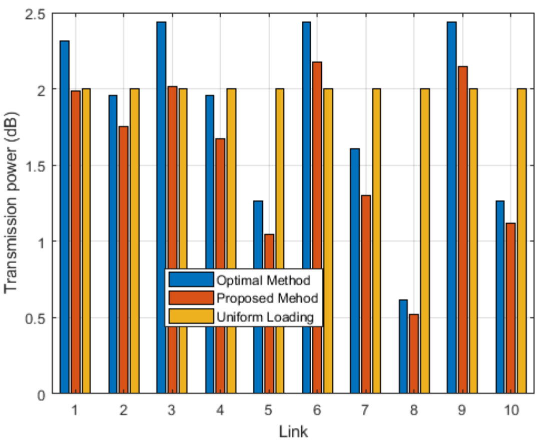

Figure 2. Allocates power to each link.

Channel capacity for all links can be calculated based on the allocated power. Figure 3 indicates the channel capacity for all links between M.U. and 10 ARUs. Optimal solution has the best performance, while uniform loading has the worst performance. By comparing Figures 2 and 3, we can conclude that allocating more power does not guarantee higher capacity. For example, for some links, transmit power based on the uniform loading algorithm is more than allocated power based on optimal and suboptimal algorithms, while in corresponding links, the uniform loading algorithm has the least capacity. In addition, we observe that it serves in some links; for instance, in link 5, channel capacity based on uniform loading is higher than that of han other algorithms. These results are expected because our goal is to maximize the overall transmission rate, and maximizing capacity at each link is behind this research scope. Figure 4 indicates the total capacity for all algorithms. It is observed that the optimal algorithm has the best performance, while the suboptimal algorithm performs better than the uniform loading algorithm. Figure 5 indicates the performance of all algorithms for different values of Pmax. The optimal algorithm can give the highest value for channel capacity, while channel capacity obtained by a suboptimal algorithm is more than that obtained by a uniform loading algorithm. In addition, this figure indicates that increasing the maximum allowable power for all algorithms increases channel capacity.

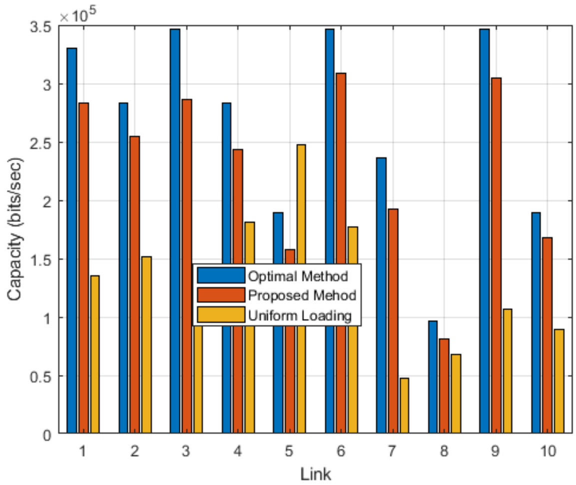

Figure 3. Channel capacity at each link

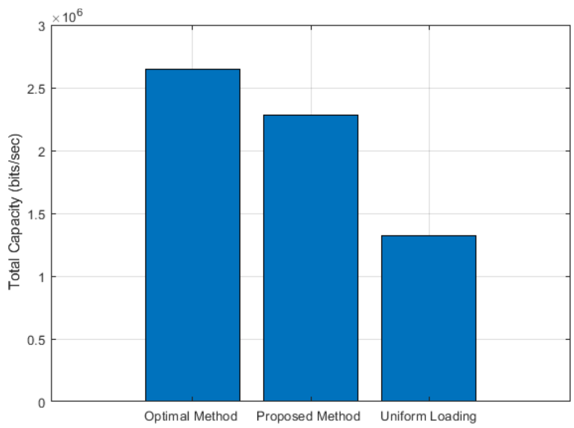

Figure 4. Overall channel capacity for all algorithms

Table 1 provides the optimal, uniform loading complexity and the proposed suboptimal algorithms. In this table, M indicates the number of ARUs, and N indicates the number of M.U.s in the network. The optimal solution has the highest Complexity because all M.U.s and ARUs must be considered. Both suboptimal and uniform loading algorithms have equal Complexity, while the suboptimal algorithm performs better.

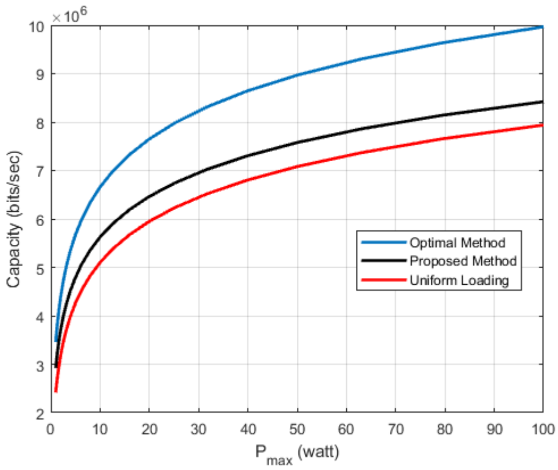

Figure 5. Channel capacity vs. P_{max} for all algorithms

Table 1. Complexity of algorithms

Algorithm	Complexity
Optimal	O(M×N)
Suboptimal	O(M)
Uniform loading	O(M)

5. Conclusion

Because of the importance of wireless cooperative networks in the future cellular network, in this paper, we investigate power allocation in dense wireless cooperative networks where many nodes are placed in small areas. Power allocation aims to calculate transmit power based on channel variations to maximize channel capacity in all situations. In this research, we calculate optimal transmit power for M.U.s using the Lagrange method for convex optimization problems. In addition, due to the Complexity of the optimal solution, we introduce a novel suboptimal algorithm. In the simulation results section, we evaluate optimal and suboptimal methods and indicate that although the optimal solution has better performance due to the less Complexity of the suboptimal method, this method is more appropriate for practical usage. Also, simulation results indicate that the suboptimal algorithm performs better than the uniform loading algorithm, where equal power is allocated to all M.U.s.

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