Channel Power Allocation Optimization Based on Water-filling Algorithm in 5G

Song Wei1,a,†, Zige Zheng2,b,†, and Chenwei Wu3,c

1 College of Information Science and Engineering, Huaqiao University, Fujian, Xiamen, PR China
2 School of Science and Engineering, The Chinese University of Hong Kong, Shenzhen, PR China
3 Institute of AI and Robotics, Academy for Engineering & Technology, Fudan University, Shanghai, PR China
1615231038@stu.hqu.edu.cn, bzigezheng@link.cuhk.edu.cn, cwwu19@fudan.edu.cn
†These authors contributed equally.

Abstract. Since entering the information age, the popularity of mobile communication has become higher and higher, and people’s requirements for communication quality are also increasing, but the channel resources that people can control are limited. This paper proposes an optimization algorithm for channel resource allocation based on water-filling algorithm. Some improvements have been made on the basis of the original water-filling algorithm. The sgn function is used to optimize the transmit interference temperature limit (Sk), so that the screening result is not completely dependent on Sk, which improves the flexibility of channel screening and effectively optimizes the capacity of the communication network.

1. Introduction
Since the development of communication technology, people continue to pursue more efficient and convenient communication methods. In ancient times, people tried to send messages by horse or pigeons. However, the amount of information transmitted through these methods was very limited, and the efficiency of information transmission was easily affected by the external environment. In 1884, with the invention of the Morse code by the American S.B. Morse, people started the era of using electricity to communicate (telegraph). Then, along with the improvement of electromagnetic wave theory, in 1896, people used electromagnetic waves for long-distance communication for the first time. Since then, the era of wireless communication has come [1].

Cellular network [2] is the foundation of modern mobile communication technology, and its concept was put forward by Bell Labs in the 1970s. Cellular network has the advantages of frequency reuse and cell splitting. The first-generation mobile communication system (1G) was born in 1986. It mainly adopts analog signal transmission technology and frequency division multiple access (FDMA). The second-generation mobile communication system (2G) is based on digital technology. In order to improve the comprehensiveness of communication services, the third-generation mobile communication system (3G) has added services such as image, music and video. In order to meet the requirements of multimedia services and higher speed data processing, the fourth-generation mobile communication system (4G) was born. 4G technology has been able to basically meet the needs of people’s work and life. In order
to further improve the convenience of life, the related technologies of the fifth-generation mobile communication system (5G) have been improved not long ago. The 5G era of "interconnection of all things" is coming.

Generally, channels are distinguished in the frequency domain and time domain. With the popularity of mobile terminal products such as mobile phones and the growth of the population (especially in China), the demand for communication is increasing. Although the frequency domain is infinite in theory, the frequency domain that people can use is limited, constrained by hardware conditions and related technologies. Therefore, in the field of modern mobile communication, frequency division multiplexing is a very important technology. In order to make better use of channel resources, predecessors have made many attempts. For example, the auction algorithm based on game theory [3], which finds a Nash equilibrium strategy for some normal channels, can effectively improve the throughput of the communication system and lead to Pareto optimal allocation.

In many traditional channel resource allocation algorithms, one channel of a cell’s base station can only serve one user, and the number of service users at the same time is completely limited by the number of channels in the cell. This is not conducive to the full use of channel resources. However, the iterative water-filling algorithm [4] can solve this problem well. A water-filling algorithm is often used to solve the problem of power allocation. The design of the water injection algorithm is based on the specific situation, while Xing and Jing et al. proposed a design method of water-filling algorithm based on different sub-channel changes [5], which provides a reference for the design of various water-filling algorithms.

In the scenario of channel power allocation, the water-filling algorithm can allocate power for multiple channels according to the specific situation of the channel, effectively improve the throughput of the network, and get rid of the constraint of the number of channels on the number of users to a certain extent, and get higher network capacity. Channel resource allocation strategy based on water-filling algorithm has been proposed continuously. For example, Shi et al. have proposed an improved power allocation water-filling algorithm [6], which avoids the iterative calculation in the traditional water-filling algorithm, effectively simplifies the algorithm and reduces the calculation amount; Chaeriah et al. proposed a power allocation method based on OFDM technology and applied water flooding algorithm in cognitive radio (CR) network for fading channels [7]. This method can effectively improve the channel performance in the network. In addition, the water-filling algorithm can also be applied to the resource allocation of multi-carrier uplink NOMA systems [8].

In the case of random channel state, only using water-filling algorithm cannot make full use of channel resources. Therefore, a parameter (Sk) can be introduced to select the channel with better quality and abandon the channel with poor quality. In this way, each user can get a better communication effect.

In this paper, a more intelligent optimization algorithm is proposed, which optimizes the parameter Sk and performs channel screening more flexibly for each user. Moreover, compared with the traditional channel allocation algorithm and other channel resource allocation methods based on the water-filling algorithm, we can obviously show the superiority of the optimization algorithm, and effectively improve the capacity of the system. In addition, the simulation results are processed by linear regression to find out the parameters which have the greatest impact on the channel capacity.

This paper is organized as follows. Section 2 is the introduction of channel resource allocation algorithms. We introduce the concept of cluster and cell, traditional channel allocation algorithm IFRN (a channel only serves one user at a time), water-filling algorithm, channel resource allocation algorithm based on the water-filling algorithm, and optimization algorithm. Section 3 is the analysis of simulation results. Under different conditions (SNR, Sk, β, etc.), the algorithm results (channel capacity), which shows the superiority of the optimization algorithm. Moreover, the influence factors of the optimization algorithm are processed by linear regression, and the characteristics of the optimization algorithm are deeply analyzed. Section 4 gives a conclusion. We give the reasons for the results of various algorithms in section 3, summarize and analyze the advantages of the optimization algorithm, and list the shortcomings of the optimization algorithm, and also put forward the possible development direction and more possibilities of the algorithm.
2. Channel resource allocation

2.1. Area coverage and cell allocation

There is a loss in signal transmission, and the transmission loss increases with the increase of distance, and will be affected by the terrain. Therefore, the communication distance between mobile client and base station is limited. In order to expand the service area, make the service area get seamless coverage, and improve the system capacity, we must use multiple base stations to cover the given service area (the coverage area of each base station is one cell). We need to choose the best cell partition method.

Divide cells in a flat area, usually forming a cellular network. To cover a plane area with regular polygons without gaps and overlaps, the only available shapes are regular triangles, squares, and regular hexagons. Hexagons are considered to cover the largest area with the least number of nodes. Its performance is superior. The mobile communication network with a hexagonal cell shape is called a cellular network. Figure 1 is the schematic diagram of three cell shapes, and table 1 shows the comparison of their attributes. In this paper, a cellular network composed of seven cells is adopted. Each cell contains a base station to provide services for the cell, as shown in Figure 2.

Each cell has its channel (frequency) configuration, namely channel set. They may be consistent or different, depending on different channel allocation methods.

![Cell shapes](image1)

**Figure 1. Cell shapes**

|                  | Regular triangle | square | Regular hexagon |
|------------------|------------------|--------|-----------------|
| Adjacent cells   | $r$              | $\sqrt{2}r$ | $\sqrt{3}r$    |
| distance         |                  |        |                 |
| cell area        | $1.3r^2$         | $2r^2$ | $2.6r^2$        |
| Overlap width    | $r$              | $0.59r$ | $0.27r$         |
| Overlapping area | $1.2\pi r^2$     | $0.73\pi r^2$ | $0.35\pi r^2$ |

![Distribution diagram of a regular hexagon cell](image2)

**Figure 2. Distribution diagram of a regular hexagon cell**

2.2. Composition of the cluster

In order to avoid co-frequency interference between cells, adjacent cells are not recommended to use the same channel. Moreover, in order to ensure sufficient distance between cells using the same channel, adjacent cells will not use the same channel. These cells that use different channels form a cluster.
2.3. IFRN
IFRN is a relatively primary channel allocation method. N is the reuse factor, that is, the number of cells in a cluster. In IFRN, each cell is allocated a fixed channel according to N, and each channel only serves one user at a time. Therefore, the number of service users of each base station strictly depends on the number of channels, and whether the bandwidth resources are unlimited. Therefore, IFRN channel allocation method lacks flexibility, and the number of users it serves is extremely limited. Figure 3 shows the channel distribution of each cell when N = 3 (different colors represent different channel sets).

For example, the total number of channels is 18, the channel numbers are 1~18, and f1=1,2,3,4,5,6; f2=7,8,9,10,11,12; f3=13,14,15,16,17,18. Each cell can only serve 6 users at the same time.

In IFRN, although the same frequency interference between cells can be reduced by selecting a larger N, it cannot be completely eliminated. The calculation formula is as follows.

\[ I_n = \sum_{m \neq n} p_{m,n} |h_{m,n}|^2 p_m \]  \hfill (1)

The subscripts m and n denote the cell number; h is the channel strength; p is the base station signal transmission power, and \( \rho \) is the interference coefficient between cells. Because the transmission loss increases with the increase of distance, the interference decreases with the increase of cell distance. In this paper, we use the cell distribution model as shown in Figure 3, N = 3, so \( \rho \) can be expressed as a matrix (\( r=0.5 \)):

\[ \rho = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & r & 0 & r \\ 0 & 0 & 1 & 0 & r & 0 \\ 0 & r & 0 & 1 & 0 & r \\ 0 & 0 & r & 0 & 1 & 0 \\ 0 & 0 & r & 0 & r & 1 \end{pmatrix} \]  \hfill (2)

We use channel capacity as the reference object to measure the performance of communication network. According to Shannon's formula, we can get,

\[ C = \log_2 (1 + SINR) \]  \hfill (3)

SINR is signal-to-interference plus noise radio. The default noise is Gaussian white noise. Therefore, the capacity formula of each cell is as follows,

\[ C_n = \log_2 \left( 1 + \frac{\sum_{m \neq n} p_{m,n} |h_{m,n}|^2 p_n}{\sum_{m \neq n} p_{m,n} |h_{m,n}|^2 p_n + \sigma^2} \right) \]  \hfill (4)

\( \sigma^2 \) is the noise signal power (i.e. variance). The total capacity of communication network is,

\[ C_{total} = \sum_n C_n \]  \hfill (5)

2.4. Water-filling algorithm
The IFRN method is rigid and inflexible, and cannot make full use of frequency resources. Even if there are abundant frequency resources, it cannot be used to improve the capacity of active users. In order to get higher channel capacity and serve more users under the same conditions, we can consider abandoning a channel while only serving one user at the same time. When users communicate, each channel is allocated a certain amount of power. Multiple users can be online at the same time, which greatly reduces the limit of the number of channels to the number of users. So how to allocate power is a topic worthy of discussion. The power allocation method based on the water-filling algorithm is a
more intelligent method. The water-filling algorithm, as the name implies, is to inject water. Each channel is treated as a bottle, and a certain amount of water is added into it, that is, power. The amount of power allocated is determined by water level and noise to Carrier Ratio. The relationship is shown in Figure 4.

![Figure 4. Channel power allocation based on water-filling algorithm](image)

According to the above water-filling algorithm, the channel capacity used by each user is as follows,

$$C = \max_{P_f} \sum_{f=1}^{10} \log_2 \left(1 + \frac{P_f|H[f]|^2}{\sigma^2}\right)$$

(6)

Because the channel strength and noise power are random, and the transmission power of each channel is allocated according to wl (water level) and noise to carrier ratio. The larger noise to carrier ratio is, the worse the channel quality is, and less power can be allocated, and more power can be allocated to the channel with better quality. This can significantly improve the quality of communication. Therefore, the selection of wl is very important to network performance and communication capacity, and the following conditions should be met.

$$P_f = \max\{0, wl - \frac{\sigma^2}{|H[f]|^2}\}$$

(7)

$$P = \sum_f P_f$$

(8)

When the noise to carrier ratio of the channel is greater than wl, the channel is abandoned, and the power is allocated to other channels with better quality. For all users in the network, we repeatedly optimize the channel power allocation for each user until the wl of each user converges to the optimal value to maximize the cell capacity.

2.5. Transmit interference temperature limit (Sk)

On the basis of using a water-filling algorithm for channel power allocation, we can make more attempts. We can introduce a new parameter Sk to make the power allocation scheme more flexible. In the conventional water-filling algorithm, although wl is determined according to the channel conditions, for some channels whose noise to carrier ratio is less than wl, but with poor quality, the final power allocated to them is very small, which is of little significance. The role of Sk is to identify such channels, help us further eliminate the channels with higher noise to carrier ratio, limit the transmission interference in the communication process, and improve the channel capacity. With the introduction of SK, the transmission power of the channel changes to,
\[
P_f = \begin{cases} 
\max \left\{ 0, w_l - \frac{\sigma^2}{|H[f]|^2} \right\}, & \text{if } S_k \geq \frac{\sigma^2}{|H[f]|^2} \\
0, & \text{if } S_k < \frac{\sigma^2}{|H[f]|^2}
\end{cases}
\]  

(9)

\[P = \sum_f P_f\]  

(10)

2.6. Self-optimizing \( S_k \)

In the previous method, \( S_k \) is set to a fixed value. However, in circumstances where the noise power for a user is relatively large in general, a small \( S_k \) value will filter out a large proportion of the channels, leaving limited options for the water-filling algorithm to allocate, and therefore negatively influence the rate of convergence and even affect the total capacity. Hence, we aim to set the value of \( S_k \) in a more flexible way to deal with this problem.

Since \( w_l \) is obtained by repeated optimization process, a successive solution of power allocation is similar to the prior solution for a certain user giving that the rate of convergence is slow. Hence, we can record which channels were assigned power in the previous solution for each user, to predict which channels are inclined to be assigned power in the current solution, and therefore personalize the value of \( S_k \) for the given user according to the noise power in these channels.

By using \( \text{sgn}(p_k[n]) \) to denote whether channel \( n \) was assigned any power to the \( k^{th} \) user, we can obtain the average noise power of the active channels for a given user. This value is multiplied with a customized multiplier \( \beta \), and then compared with \( S_k \) value. Hence \( \tilde{S}_k \) for the current optimization problem is set as the following,

\[\tilde{S}_k = \max(S_k, \beta \cdot \frac{\sum_{n=1}^{N} I_k[n] \cdot \text{sgn}(p_k[n])}{\sum_{n=1}^{N} \text{sgn}(p_k[n])})\]  

(11)

3. Results and analysis

3.1. Simulation environment

By default, experiments are conducted in a 7-cell network, with 3 users per cell on average and 18 frequency channels. The average SNR of the channels is set to 15.

SNR values in the channels and the numbers of users in cells are randomly generated following normal distribution to simulate the network. For parameters of each distinct value, we conduct 100 repeated simulations on the network and record the mean value of the results as the capacity performance output.

3.2. Control group

As the basic method of \( S_k \) and the self-optimizing method, SWF is simulated in the network first. A capacity performance of 31.59 is observed, which is defined as the control group in comparison with the following methods in the experiments.

3.3. Comparison and analysis

We tested the performances of assigning different fixed \( S_k \) values from 0.3 to 4. Larger \( S_k \) values are also tested to further observe the tendency. The result is shown in Figure 5.
Figure 5. Capacity performance on Sk without self-optimizing

We can easily observe that when Sk is set to relatively large values, capacity drops below 32 and remains on that level, demonstrating a similar performance as that of the SWF method (31.59). An averagely high-capacity performance above 35 is observed when Sk is set to 1.2 or lower values.

Since a steady decrease in capacity is observed when Sk is in the range from 0.3 to 4, to further reveal the effect of Sk value on capacity, we did linear regression based on ordinary least square method on the data that fall in this range. The result is shown in Figure 6.

Figure 6. Result of linear regression on Sk

We consider this fitted result unsatisfying, for the data of Sk in the range from 0.3 to 1.1 shows a lower rate of decrease. In other words, although capacity drops slightly in this range, the extent is limited. As Sk further increase, we can observe a more obvious linear negative correlation with a considerable rate of decrease. Hence, we did separate linear regression based on the data of Sk falling in the range from 0.3 to 1.1 as well as from 1.1 to 4. The results are shown in Figure 6.

The latter result shows a slope with a larger absolute value of 0.975, compared with the former result 0.252. From this experiment, we can conclude that the effect of further decreasing Sk to lower than 1.1
is limited, and that Sk can be considered to have a considerable negative linear correlation with capacity performance in the region from 1 to 4.

We also noticed that the computing time of the simulation is significantly longer for low-value Sk. For Sk lower than 0.5, the run time increases significantly compared with when Sk takes value in 1 or larger, signifying that more computation power is required for a solution of allocation to be found. Considering that the performance improvement of decreasing Sk from 1.1 to smaller values is low, while the increase in required computation time is significant, it is an inefficient way to further improve the capacity by setting Sk to extremely low values. Thus, in our following experiments, Sk is set to 1 by default.

Sk can be considered as a filter for the frequency channels of the network. By setting a lower Sk, we can identify and then ignore the channels with noise power larger than the defined level, and enable only the channels with low noise power for each user. Thus, the total power is distributed to a limited number of high-quality channels based on SWF. In this way, the optimal channels for each user are found in the network. However, considering that repeated optimization needed to be conducted to find the optimal water-levels for all users, a small value of Sk will significantly limit the number of channels available for each user, therefore limit the possible range of the calculated water-level. Added with more constraints, the rate of convergence will inevitably decrease when we wish to simultaneously optimize the water-levels of all users in the network. In an extreme case, when Sk is set low in a crowded network, we may encounter a situation in which no optimal solution can be found for the network. Hence, to optimize the network, a relatively small Sk is preferred as long as it falls in a reasonable range.

We further tested how the self-optimizing method can improve the capacity with different values of $\beta$. Sk is set to 1 in this experiment to analyze the performance of the network with a satisfying rate of convergence. The result is shown in Figure 7. As a control group, we note that the capacity performance of Sk=1 without self-optimizing from the previous experiment is 35.13.

![Figure 7. Capacity performance on $\beta$ when Sk=1](image)

Capacity performance is further improved when beta is in the range from 0.9 to 1.2, with the best performance of 36.29 observed at $\beta=1.1$.

Meanwhile, we can observe an obvious negative correlation between $\beta$ and the capacity for $\beta$ larger than 1.1. It appears that the rate of descent decreases slightly as $\beta$ is set to larger values. We also did linear regression on the experiment data for $\beta$ larger than 1. The result is shown in Figure 8.
We can infer from the slope that capacity decreases as $\beta$ increases, it also seems that the rate of decrease seems to be decreasing as well. Hence, we did separate regression on the regions where $\beta$ is smaller or larger than 2.5. The results are shown in figure 7.

They show that as $\beta$ increases, the rate of decrease in capacity drops, with a slope of -1.793 for the first group of data and a slope of -0.69 for the second. Given this result, we can anticipate that as $\beta$ further increases, the rate of decrease in capacity may converge to zero, signifying that the capacity performance for large $\beta$ may converge to a certain level. This will be discussed in the following paragraph.

In this experiment, we noticed that for small valued $\beta$, the capacity performance decrease as $\beta$ decreases, and converges to the result under a fixed Sk=1 environment. The peak performance is further improved compared with non-self-optimizing methods. However, if $\beta$ is set to higher than 1.8, it negatively affects the performance of the network, with a result lower than the fixed Sk=1 experiment. Recall the formula (10), and we can obviously conclude that if $\beta$ is set to a considerably small value, the result of this function would most likely be Sk, which would have no obvious difference from setting Sk to a fixed value as in the previous method. This is proved by the experiment result above, specifically the result of small $\beta$ values. Meanwhile, although higher $\beta$ can enable more channels for users under the influence of large noise power, it may negatively affect other users in general. If $\beta$ is high enough, multiplied with the average effective interference power, the second element in the maximum comparison will overwhelm the fixed Sk value in some cases, despite that the noise power is not high enough to cause influence. For these users, we can infer the negative effect on capacity by setting some higher fixed Sk values for them. Hence a high $\beta$ value would affect the capacity performance. From this experiment, we can infer that this influence is considerable and should not be neglected. Theoretically, in extreme cases, when $\beta$ is set to significantly high values, the negative effect of this $\beta$ will counteract the positive effect of introducing Sk. Hence, as mentioned before, we can anticipate that for larger $\beta$ values, the capacity should converge to the result of SWF method.

Therefore, to maximize the positive impact on capacity performance, the optimal $\beta$ should vary based on the natures of the network, and in this case, it should fall in the range from 0.9 to 1.2. Thus,
the default value for $\beta$ in our following experiments is set to 1.1. Conducting experiments before setting $\beta$ is highly recommended during implementation in general networks.

From the two conducted experiments, we can conclude that introducing $Sk$ and $\beta$ can indeed improve the performance of the network, given that appropriate values of the parameters are chosen. We further did experiments on the stability of the self-optimizing method. In specific, we ran the network while varying SNR as well as the average number of users per cell, respectively.

The capacity result under a $Sk=1, \beta=1.1$ network with different SNR values is shown in Figure 9.

![Figure 9. Capacity performance on SNR in a self-optimizing network (Sk=1, $\beta=1.1$)](image)

It is observed that capacity maintains on a certain level when SNR exceeds 14. A linear correlation can be observed when SNR is in the range from 1 to 14. The result is shown in Figure 10.

![Figure 10. Result of linear regression on SNR in specified range](image)

The slope for SNR<14 is 1.576, which is significantly larger than the slope for larger SNR values, 0.039. This indicates that unless the SNR value is relatively low (below 14), the positive effect on capacity by increasing SNR is extremely limited. Considering that if a satisfying SNR is already obtained, the cost and complexity of further increasing SNR is relatively high. Hence, introducing the self-optimizing method is an efficient way of improving network capacity in this circumstance.

We then tested the network performance while varying the average number of users per cell. The result is shown in Figure 11.
Compared with the IFR method which has been proved to perform poorly in networks with large number of users, the self-optimizing method inherits the advantage of SWF method, giving steady satisfying performance in both densely populated networks as well as sparsely populated ones.

Another observation in these conducted experiments is that the computation of the self-optimizing method is indeed more efficient compared with the fixed Sk method, as shown in Table 2.

| Run time (100 simulations) | Fixed Sk=0.3 | Fixed Sk=0.5 | Fixed Sk=1 | Sk=1, β=1.1 |
|---------------------------|--------------|--------------|------------|--------------|
|                           | 4271 s       | 2990 s       | 1864 s     | 1616 s       |

Given our aim to improve capacity, we can either decrease the value of Sk or introduce the self-optimizing method with parameter β. Evidently, the computational cost of the latter method is significantly lower than the former.

4. Conclusion
Given our aim to improve the network capacity in cellular networks, without having to devote greatly to obtaining higher SNR or more frequency channels, we proposed two alternative ways that are more efficient and cost-free. We first introduced the Sk method and further designed a self-optimizing Sk method based on the SWF method for frequency power allocation. Considering the computation cost of setting low Sk values, we set Sk at a reasonable value and used the self-optimizing method to further improve the capacity of the network. The conducted experiments revealed that the positive effect of introducing β is significant when β is set to the reasonable range. An improvement in efficiency is also observed. This concludes that the self-optimizing Sk method can indeed improve the capacity performance while preserving a high computation efficiency. We should note that given the nature of different networks may vary in real-world applications, the suitable range for β should vary accordingly. In case that an inappropriate β may have no effect and even negatively affect the capacity, experiments should be conducted before determining β.

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