Graph-Based Terminal Ranking for Sparsification of Interference Coordination Parameters in Ultra-Dense Networks

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Abstract. In the future mobile communication system, inter-cell interference becomes a serious problem due to the intensive deployment of cells and terminals. Traditional interference coordination schemes take long time for optimization in ultra-dense networks. Meanwhile, due to the increase of factors affecting communication and in order to better meet the communication needs of each terminal, an interference coordination scheme needs to fully consider multiple characteristic parameters of the terminal, which will further increase the scheme's computational time. Therefore, we should compress all the data through sparsification of parameters before optimization. There are many terminal parameters, and the essence of sparsification of parameters is to rank terminals. In this paper, a graph-based terminal ranking scheme is designed. First, each terminal can be represented by its multiple parameters. Then, all terminals are used as the vertexes in the graph to form a complete weighted graph, and edge weights represent the degree of dissimilarity between terminals. A ranking of terminals is obtained by finding a minimum Hamiltonian path in the graph. Finally, the ranking of all parameter sequences is obtained according to terminals ranking, which makes the sparsity of all parameter sequences better. Simulation results show that the proposed scheme can accomplish sparsification of parameter sequences effectively, especially when the number of sequences increases. In addition, compared with the optimal coordination of traditional scheme, this scheme improves the fairness of the system while ensuring high system capacity, and dramatically reduces the computational time of interference coordination.

Keywords: Ultra-dense networks · Inter-cell interference coordination · Sparsification · Hamiltonian path · Approximation algorithm

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1 Introduction

With the commercialization of the fifth generation (5G) mobile communication system, the research on 6G wireless network will also be launched to meet the requirements of the intelligent information society in 2030 [1]. Compared with 5G, 6G will have super flexibility in the utilization of time-frequency-space resources, providing higher speed, greater capacity and ultra-low delay for applications faster than 5G in the future [2]. Ultra-dense networks (UDNs) are widely used as an effective way to increase system capacity. The intensive deployment of cells and terminals will result in intra-cell and inter-cell interference. Intra-cell interference can be avoided through clever design of transmission signals, while inter-cell interference is regarded as the main limiting factor of cellular system performance, so interference coordination will become a very important issue in ultra-dense networks [3].

In the existing researches on interference coordination, most of the literatures considered two parameters of the useful signal power and interference signal power of the terminal, and then maximized the average spectral efficiency of the network according to Shannon formula [4–6]. [7] considered the transmitting power of the terminal, inter-cell interference could be reduced by controlling power of the user at the edge of cell. Due to the increase of terminal business types, different business requirements correspond to different data rates, so the minimum data rate requirement of users was also an important parameter [8], and [9] converted the data rate requirement of users into the number of resource blocks required by users. There are a large number of mobile terminals in the cellular network, or most of the terminal devices are moving, so we should also consider the impact of terminal mobility on the network [10]. [11] proposed mobility management based on contextual information awareness. In addition, when there are terminals with low power in actual network scenes, better channels should be allocated for them, otherwise user experience will be affected. Therefore, the battery power of terminals is also an important influencing factor. To sum up, in the future mobile communication system, in order to meet the communication needs of each terminal as much as possible, interference coordination scheme need to fully consider the various factors influencing the terminal. In other words, multiple characteristic parameters of the terminal should be considered in interference coordination. Therefore, it is of great significance to study interference coordination scheme for terminal multi-parameter case.

Traditional inter-cell interference coordination schemes take long time in the ultra-dense network, especially with the increase of terminal parameters, the interference coordination time will be further increased. [12] considered interference coordination problem in the two-layer heterogeneous network, an almost blank subframe (ABS) was introduced and the original resource allocation problem was modeled as a generalized allocation problem (GAP) by fixing the ABS ratio. Then the ant colony algorithm was used to solve the problem, which can significantly improve throughput of the system. [13] studied interference coordination in ultra-dense networks from a user-centric perspective. On the one hand, the user kept away from the main interference sources to ensure that its ideal signal to interference plus noise ratio (SINR). On the other hand, the QoS requirements of users could be satisfied through priority allocation of resources. And then an iterative resource allocation scheme based on graph coloring algorithm was proposed, which proved that this scheme could improve the system spectral efficiency and the proportion of users meeting QoS requirements. [14] considered the joint optimization of mobile station unloading and interference coordination in ultra-dense heterogeneous networks, and a heuristic algorithm was proposed to solve the problem step by step. Compared with the traditional frequency-domain interference coordination scheme, this scheme could improve the signal to noise ratio and data rate of mobile stations. [15] studied energy consumption and interference coordination in ultra-dense networks, and the goal was to maximize the energy efficiency of the worst user in the cell. The original problem was transformed by relaxation method and introduction of new parameters, then the transformed problem could be solved by fractional programming and Lagrangian dual decomposition method, and finally, the solution was rounded to get the original solution. The scheme ensured good load balance and energy efficiency in ultra-dense networks.

Some researchers have tried to use intelligent methods to solve the problem of interference coordination. [16] studied interference management problem in dense small cellular networks. Base stations determined downlink transmission power by autonomously sensing the surrounding interference, aiming to minimize the total transmission power, thus forming a competitive relationship between base stations. Then the interference coordination problem was modeled as a partially observable Markov decision process, and multi-agent reinforcement learning was used to solve the problem. Finally, it was proved that this method could reduce the power consumption, and improve network performance. In [17], the problems of beamforming, power control and interference coordination in downlink cellular networks were studied, which were jointly modeled as a non-convex optimization problem to maximize the sum of signal-to-noise ratios of all users. Then deep reinforcement learning be used to solve the problem, which could greatly improve sum-rate capacity of the network. [18] provided a new way of thinking for solving interference coordination in multi-cell downlink communication, which was to make full use of the beneficial influence of intra-cell interference and inter-cell interference. Under different coordination overhead, three schemes are proposed to make full or partial use of inter-cell and multi-user interference in the paper. All three schemes considered incomplete channel state information and therefore used probabilistic and deterministic optimization methods to minimize the total transmitted power. Finally, the paper also verified that the power consumption of these schemes is lower than that of existing schemes.

In order to reduce the time of interference coordination scheme in ultra-dense networks, we prefer to compress data first and then carry out interference coordination. Data compression refers to the use of less data to represent the original huge data, that is, the sparse representation of data [19]. In other words, the implicit information in the data can be reflected in a small number of coefficients, reducing the redundancy of data. Wavelet transform is a time-frequency analysis method with multi-resolution characteristics [20]. The high-frequency coefficients of wavelet coefficients are mostly zero or very small while the low-frequency coefficients with relatively large modulus reflect the contour information of the signal. Therefore, we can use a small amount of low-frequency coefficients to express the original signal sparsely. In order to make a small amount of low-frequency coefficients in the wavelet domain reflect various characteristics of the original data better, the data should be ranked according to certain rules, that is, the ranked data has better sparsity. The process of ranking is called sparsification of data.

According to the above analysis, sparsification of data is a key step to reduce the computational time of interference coordination scheme. [21] proposed a grouping and sorting method, which only considered useful signal power and interference signal power of the terminal, and two parameters were related to the terminal position. When multiple and random parameters of the terminal are considered, such as terminal business requirements, the performance of the scheme will be significantly reduced. [6] proposed and proved a fast matching scheme. By ranking two terminal parameter vectors, the optimal interference coordination could be achieved by using reverse matching. However, this scheme required the objective function to meet certain conditions. Sparsification of multiple parameters essentially means to rank multiple parameter sequences differently, so that multiple parameter sequences have better sparsity. But as the number of parameter sequences increases, the scheme of ranking each parameter sequence separately will make the first ranked sequence have poor sparsity. So we consider to rank multiple parameter sequences simultaneously. At the same time, due to the essence of sparsification of multiple parameters is to rank terminals, we rank terminals according to certain rules, and then get the new ranking of each parameter sequence according to the ranking of terminals. As a result, we put forward graph-based terminal ranking scheme. The idea of the scheme is to regard terminals as the vertexes in the graph, the weight of each side express the degree of dissimilarity between terminals. Terminal ranking problem can be converted to a problem of traversing all vertexes once and only once in the graph, that is, finding a Hamiltonian path in the graph. This is a classical mathematical problem in graph theory, so it can be solved quickly with the help of relevant algorithms.

The rest of this paper is arranged as follows. Section 2 describes the system model. In Sect. 3, we introduce the terminal ranking scheme based on graph and its application. In Sect. 4, the performance of the method is simulated. Finally, the conclusion is drawn in Sect. 5.

2 System Model

We consider a communication system containing multiple cells. Assuming that M characteristic parameters are used to describe each terminal, the corresponding matrix of all characteristic parameters can be expressed as

$$\mathbf{CP} = \{CP_{m,n} \,|m = 1, 2, \cdots, M; n = 1, 2, \cdots, N\}$$

where N represents the total number of terminals in the system. The optimization problem of inter-cell interference coordination can be expressed as

$$\max f(\mathbf{CP}) \tag{1}$$

where $f(\cdot)$ is the objective function of the optimization of the interference coordination problem, which can be capacity, throughput, etc. The above problems are usually NP hard, and the solution space is determined by N. Considering that the solution space of this problem is very large, the time to obtain an approximate optimal solution should be extremely long, so that traditional search algorithms are difficult to find a near-optimal solution within an acceptable computational time.

As shown in Fig. 1, multilayer wavelet decomposition is performed for each row in **CP** to retain the wavelet transformation coefficients of each layer and the scaling transformation coefficients of the last layer to form a new matrix **CPW**. Only the scaling transformation coefficients are retained to form a new matrix, written as

$$\mathbf{CPS} = \{CPS_{m,n} \,|m = 1, 2, \cdots, M; n = 1, 2, \cdots, NS\}$$

where NS is the length of the remaining scaling transformation coefficient vector of N after the wavelet decomposition of layer L, which can be approximately expressed as $NS \approx N/2^L$.

The parameters after the above wavelet decomposition processing are used for the interference coordination optimization problem, and can be expressed as

$$\max f(\mathbf{CPS}) \tag{2}$$

Since the solution space of (2) is determined by NS, which is much smaller than (1), the computational time must be greatly reduced.

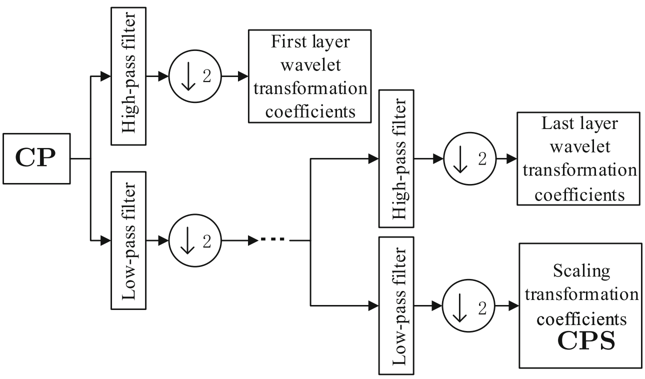


Fig. 1. Discrete wavelet transform process.

In the process of wavelet decomposition, the terminal characteristic information represented by the original parameter matrix should not be discarded too much, and the original parameter matrix information extracted by the retained scaling transformation coefficients is closely related to the rank of these parameters. These parameters describe the characteristics of terminals, and the ranking of parameters is determined by the ranking of terminals. So we are committed to designing a terminal ranking method.

This paper adopts graph theory to model the problem. Terminals are the vertexes of the graph, vertex set $\mathbf{V} = \{v_n | n = 1, 2, ..., N\}$ represents N terminals, edge set $\mathbf{E} = \{(v_i, v_j) \,| i, j = 1, 2, \cdots, N, i \neq j\}$ represents the degree of difference between any two terminals, and the weight of edge (v_i, v_j) is denoted as $w_{i,j}$. Considering that there is only one terminal sequence and there are multiple parameters affecting its ordering, the numerical values of multiple characteristic parameters can be used to solve ranking problem of terminal sequence. The weight of each side is the Euclidean distance calculated according to parameter values between terminals, which is expressed as $w_{i,j} = (\sum\limits_{m=1}^{M} (\overline{CP}_{m,i} - \overline{CP}_{m,j})^2)^{\frac{1}{2}}$, where $\overline{\cdot}$ represents the normalization processing of corresponding parameter values. After the above processing, the scenario is represented as an undirected complete graph $G = (\mathbf{V}, \mathbf{E})$. Then the graph theory knowledge is used to find a ranking strategy of the terminal, written as $A = \{A(n) \,| n = 1, 2..., N\}$, where $A(n)$ is the terminal number that ranked the n-th position. Therefore, the sparsity of the characteristic parameter matrix after ranking is better.

The smaller the distance between two terminals, the closer the corresponding characteristic parameters of two terminals are. The sequential arrangement of the terminals with close Euclidean distance can make the parameter vector redundant as far as possible, and the scaling transformation coefficients can be extracted easily. Therefore, the ranking result of terminals should satisfy the requirement that the distance between any two adjacent terminals should be as small as possible, then the terminal ranking problem is transformed into the problem of finding the minimum Hamiltonian path, which is expressed as

$$A^* = \underset{A}{argmin} \sum_{n=1}^{N-1} w_{A(n),A(n+1)} \tag{3}$$

where A^* is the optimal ranking strategy of terminals.

3 Graph-Based Terminal Ranking Method

3.1 The Proposed Method for the Minimum Hamiltonian Path

Formula (3) indicates that solving the minimum Hamiltonian path is an NP hard problem [22], which cannot be solved in polynomial time. We can get a minimum Hamiltonian cycle and then remove an edge to get a Hamiltonian path (usually removing the edge with the largest weight).

There are two common algorithms to find the minimum Hamiltonian cycle of a complete graph. One is search algorithm, such as simulated annealing algorithm, genetic algorithm, etc. The other is approximation algorithm, such as nearest neighbor algorithm, double spanning tree algorithm and Christofides algorithm. The upper limit of approximation ratio is $\frac{1}{2}(\lceil \log_2 N \rceil + 1)$, 2 and 1.5 respectively [23–25]. Among them, the search algorithm can get an approximate optimal solution, but when the number of terminals is very large, the search process takes too long time, which violates our original intention of reducing the time of the interference coordination scheme. Therefore, we prefer to use approximation algorithm to get a better solution of the above problems in a short time. The approximation ratio is used to measure approximation algorithms running in polynomial time and ensure the ratio of the cost of approximation algorithm to optimal cost [26].

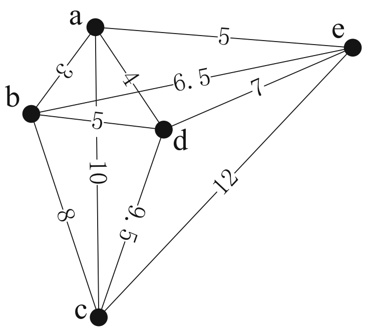


Fig. 2. Complete weighted graph.

The detailed steps of the three approximation algorithms are described below, and each of them is used to solve the complete graph shown in Fig. 2. In order to compare the advantages and disadvantages of the solutions of the three algorithms, we use the exhaustive method to calculate that the optimal solution in Fig. 2 is *abcdea* with weight of 32.5, and the worst solution is *acebda* with weight of 37.5.

Nearest Neighbor Algorithm(NNA)

Step 1. Select any point $v_1 \in \mathbf{V}$, use $\mathbf{H}$ to store the minimum Hamiltonian cycle found and initialize it as $\mathbf{H} = \{v_1\}$, and set the unselected vertices as $\tilde{\mathbf{V}} = \mathbf{V} \backslash \mathbf{H}$;

Step 2. Set $\mathbf{H} = \{v_1 v_2 \cdots v_i\}$, pick the next point $v_j^* = \underset{v_j \in \tilde{\mathbf{V}}}{argmin}\, w_{i,j}$, the new minimum Hamiltonian cycle is denoted as $\mathbf{H} = \left\{v_1 v_2 \cdots v_i v_j^*\right\}$, and update the set $\tilde{\mathbf{V}}$;

Step 3. If $\tilde{\mathbf{V}} = \emptyset$, stop, obtain an approximate minimum Hamiltonian cycle, denoted as $\mathbf{H} = \mathbf{H} + \{v_1\} = \{v_1 v_2 \cdots v_N v_1\}$. Otherwise, go to Step 2.

Taking the complete graph in Fig. 2 as an example, and set a as the starting point, a Hamiltonian cycle *abdeca* with weight of 37 can be obtained. The solving process is shown in Fig. 3, where the bold line represents the selected edge and the arrow represents the selection order of each vertex.

Thus, it can be seen that when the nearest neighbor algorithm is used to solve the problem, the edge with the lowest current weight is selected each time to get the next vertex, which will make the selection of the last two edges unique. If one of the edges has a large weight, the approximate solution will be poor. Therefore, the approximate solution obtained by nearest neighbor algorithm may have a certain gap from the optimal solution.

Double Spanning Tree Algorithm(DSTA)

Step 1. Find a minimum spanning tree T of complete graph G;

Step 2. Double its edges to get an Euler diagram G^*;

Step 3. Find an Eulerian cycle $\mathbf{E_v}$ of G starting from some vertex v, that is, a cycle that goes through each edge of the graph once and only once;

Step 4. Starting from v and visiting each vertex of G along $\mathbf{E_v}$. In this process, once a duplicate vertex is encountered, it is skipped straight to the next vertex, until all the vertices have been accessed.

Taking Fig. 2 as an example, a minimum spanning tree is first obtained, as shown in the thick line in Fig. 4, and then double its edges to obtain an Euler diagram, as shown in Fig. 4. Then an Eulerian cycle starting from point a is *aeadabcba*, and the final Hamiltonian cycle is *aedbca* with the weight of 35.

Because there are many Eulerian cycles, the Hamiltonian cycles obtained are not unique. However, some distant points will not appear continuously in any closed trace (such as *ac*, *ec*), so these poor edges will not appear in the final Hamiltonian cycle, which guarantees the performance to a certain extent.

Christofides Algorithm(CA)

Step 1. Find a minimum spanning tree T of complete graph G;

Step 2. Set the set of odd-degree vertexes in T as $\hat{\mathbf{V}}$, find the minimum-weight perfect matching of the derived subgraph of $\hat{\mathbf{V}}$ (that is, the match that contains all vertices and has the minimum sum of matching edge weights), add these matching edges to T to get Euler diagram G^*;

Step 3. Find an Eulerian cycle $\mathbf{E_v}$ of G starting from some vertex v, that is, a cycle that goes through each edge of the graph once and only once;

Step 4. Starting from v and visiting each vertex of G along $\mathbf{E_v}$. In this process, once a duplicate vertex is encountered, it is skipped straight to the next vertex, until all the vertices have been accessed.

Taking Fig. 2 as an example, a minimum spanning tree is first obtained, as shown in the bold line in Fig. 5. Find out the odd-degree vertexes, as shown circled vertexes in Fig. 5. Find its minimum-weight perfect matching as $\{ae, cd\}$, add matching edges to T to get Euler diagram G^*. An Eulerian cycle from point a is *aeadcba*, and finally Hamiltonian cycle is *aedcba* with the weight of 32.5.

Similar to double spanning tree algorithm, Christofides algorithm also uses the minimum spanning tree and Euler diagram, which can avoid selecting the edge with large weight. Christofides algorithm can obtain an Euler diagram by

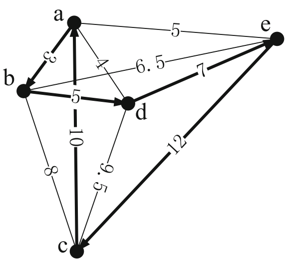


Fig. 3. The optimal solution obtained by NNA.

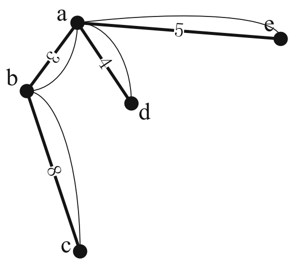


Fig. 4. Euler diagram in DSTA.

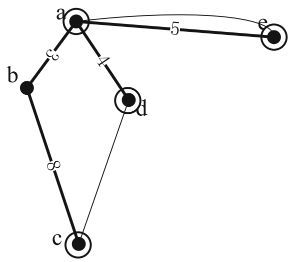


Fig. 5. Euler diagram in CA.

adding a small number of matching edges, so that the final approximate solution may be better and the time required to find Eulerian cycle is lower.

3.2 Application of the Proposed Method for Inter-Cell Interference Coordination

In the future, the number of terminals in ultra-dense networks is usually large, and the service transmission delay of terminals is usually small. After confirming which terminals have service transmission, resource management needs to be completed within a very short time, that is, corresponding to the millisecond resource management cycle. Therefore, the above algorithm cannot be directly applied to rank the terminals within the resource management cycle.

Further considering the characteristics of terminal mobility, position, power, business flow and so on in these scenarios, the change period is usually much larger than the millisecond level. Therefore, we can adopt a terminal ranking process with a larger level of cycle to rank all terminals in the system. Then, when the terminals requiring business transmission are processed in a resource management cycle, the ranking is not needed anymore. Instead, the ranking of these terminals can be obtained directly from the ranking of all terminals, which solves the problem that terminals ranking cannot be completed in resource management cycle of milliseconds.

The specific process is shown in Fig. 6. First, the parameters matrix of terminals is updated in real time according to their constant change. When a large cycle update is reached, the graph-based terminal ranking method proposed in this paper will be used to rank all the terminals in the system, so as to obtain a long cycle of terminal ranking results. Then, during each resource management cycle, terminals requiring coordinated interference are identified according to business requirements, and the order of these terminals is determined based on the ranking results of the long cycle. Final, the matrix formed by these terminal characteristic parameters is transformed by discrete wavelet transform, and the scaling transformation coefficients are used for interference coordination. Since the length of the scaling transformation coefficient vector is much smaller than the number of these terminals, the computational time of interference coordination can be greatly reduced.

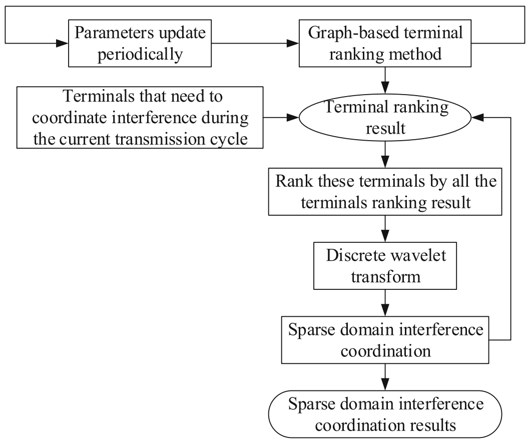


Fig. 6. Application of terminal ranking method to interference coordination.

Note that this process may involve the optimization objective function calculated by scaling transformation coefficients, may also involve in adopting discrete wavelet inverse transform to return the interference coordination result corresponding to the scaling transformation coefficients to the terminal coordination result, etc. But these are necessary steps in interference coordination scheme. This paper focus on the terminal ranking in order to adopt the best way to extract the scaling transformation coefficients of the terminal characteristic parameters, so the steps involved in interference coordination are not described in detail here.

In the application scheme shown in Fig. 6, it is necessary to ensure that the large cycle is much larger than the small cycle, so as to make the proposed scheme effective. The update cycle of terminal parameters is much larger than a resource management cycle, so that several or dozens of resource management processes can be effectively carried out within a large cycle. If the terminal parameters are updated frequently, the proposed scheme is no longer applicable. Therefore, the proposed scheme is suitable for communication scenarios in which the terminal is moving at low and medium speeds and the transmission service is relatively stable. In addition, the number of terminals in each cell is very large, but the large cycle is only relative to one resource management cycle. In each large cycle, not all terminals will participate in interference coordination all the time, so it is not necessary to directly handle all terminals in the cell indiscriminately. Although this is done by base station with very powerful computing power, it will undoubtedly add to the computational burden of base station. Therefore, how to dynamically manage the terminal to be ranked within each large cycle will be a practical application problem, which will further reduce the power consumption of base station.

4 Performance Evaluation

4.1 Simulation Parameters and Performance Indicators

This paper simulates a two-cell scenario, and scenario parameters are as follows: cell radius is 200 m, distance of base station is 220 m, carrier frequency is 2.0 GHz, transmitting power of terminal is 21 dBm, the power of AWGN is 174 dBm/Hz, bandwidth per resource blocks is 180 kHz, signal transmission model use close-in free space reference distance pathloss (CI-FSPL) model [27]. The proposed scheme is independent of the number of terminals and their characteristic parameters. Theoretically, the number of terminals in each cell can be set arbitrarily. However, due to the limited computing capacity of the hardware devices used in the simulation, we set the number of terminals in each cell to 500, and these terminals are uniformly distributed. The number of terminals that can be arranged for transmission varies within each resource management cycle, but the number of resource blocks that can be used by each cell within that cycle is fixed in each simulation, plotted on the X-axis of some figures, and varies between 200 and 1000. Assuming that the network is saturated, that is, all resource blocks are fully used in each cell. The interference coordination problem between two cells is mathematically reduced to a two-dimensional matching problem. The wavelet basis of discrete wavelet transform is Sym2, and the number of decomposition layers is 3.

Terminal characteristic parameters consider useful signal power, interference signal power, and terminal business requirements, among which useful signal power and interference signal power are determined by the terminal position and network parameters. Different terminals have different business requirements and need to use different number of resource blocks to meet their own data transmission. Therefore, the business requirements of terminals are transformed into the number of resource blocks required by terminals, which is represented by integer between [1,10], and generated randomly in simulation. In the following simulation, two parameters are used to refer to the useful signal power and interference signal power of terminals. The number of terminals to be coordinated in each cell within a resource management cycle is consistent with the number of resource blocks. Adopting three parameters refers to increasing the business requirements of terminals. The number of terminals in each cell that acquire transmission opportunities within a resource management cycle varies from 50 to 250, and these terminals divide the entire resource block in a random manner.

In this paper, four performance indicators are used to measure the proposed method, namely, Gini index, reconstruction error, capacity per resource block and Jain's fairness index. System capacity corresponds to the total capacity of all terminals allocated resources in the corresponding resource management period in the system. To facilitate comparison, we further take an average of system capacity to get the capacity per resource block. Jain's fairness index is the value obtained by plugging the capacity of these terminals into the Jain's fairness calculation formula [28]. These two are common indicators and will not be repeated here. The following is a brief description of the calculation of Gini index and reconstruction error in this paper.

Gini index is one of the important parameters to measure sequence sparsity [29], $\mathbf{CPW}'$ represents the matrix formed by each row in $\mathbf{CPW}$ is arranged in ascending order, and the Gini index corresponding to the coefficients of the m-th row is calculated as

$$GI_m = 1 - 2\sum_{n=1}^{NS} \frac{CPW'_{m,n}}{\sum\limits_{n=1}^{NS} CPW'_{m,n}} \left(\frac{NS - n + \frac{1}{2}}{NS}\right) \tag{4}$$

Gini index is between [0,1), which corresponds to the distribution of the wavelet coefficients of the matrix after the wavelet transform. The sparsity of the original parameter matrix $\mathbf{CP}$ is better, the more zero value (or approaching zero value) in the wavelet coefficient matrix obtained by the wavelet transform, the larger the Gini index of each row of the matrix $\mathbf{CPW}$ will be. Gini index of each row is calculated according to formula (4), and its average value is calculated as the performance indicator in this paper.

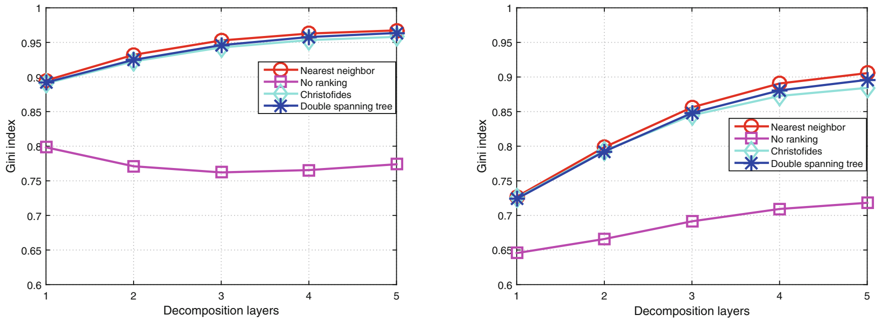
The reconstruction error reflects the gap between the reconstructed signal and the original signal [30], reconstruction error of $\mathbf{CP}$ is expressed as

$$\delta = \frac{1}{M}\sum_{m=1}^{M}\sqrt{\frac{1}{N}\sum_{n=1}^{N}\left(\overline{CP}_{m,n} - \overline{\overline{CP}}_{m,n}\right)^2} \tag{5}$$

where $\overline{\overline{CP}}_{m,n}$ represents the value after normalization by row of corresponding elements in the matrix $\overline{\overline{\mathbf{CP}}}$ reconstructed by the inverse transformation of $\mathbf{CPS}$. The sparsity of the original parameter matrix is better, which indicates that the more high-frequency coefficients in the wavelet coefficients after the discrete wavelet transform tend to zero, and the low-frequency coefficients can better reflect the characteristics of the original matrix. Therefore, the error between the matrix that is reconstructed back to primitive domain with a small amount of low-frequency coefficients and the original matrix is smaller.

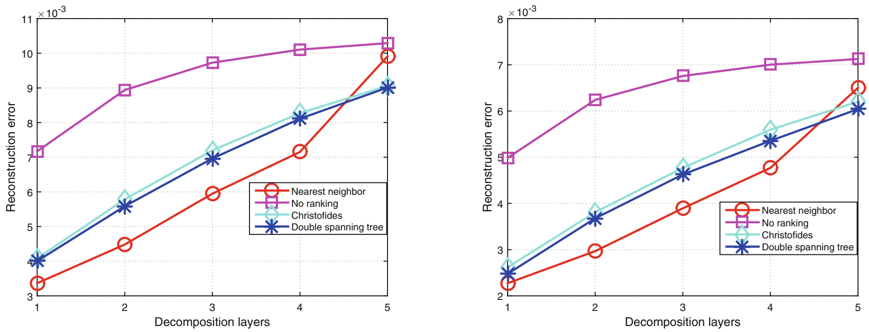
4.2 Simulation Results and Analysis

Figure 7 and Fig. 8 show the Gini index and reconstruction errors of the proposed method, and compare them with the no-ranking method. The corresponding performance of three Hamiltonian path algorithms for terminal ranking is better than that of no-ranking method, which indicates that the sparsity of parameter matrix is greatly improved after ranking. It can also be seen that the performance of the three algorithms for solving Hamiltonian path differs little. In comparison, the Gini index of the Nearest neighbor algorithm is slightly better, and the reconstruction error of the Christofides algorithm is slightly worse. In addition, when the number of decomposition layers is too large, the reconstruction error of the nearest algorithm will suddenly increase. By comparing the two sub-graphs of two figures, when the number of parameter sequences increases, the scheme of ranking the parameter sequences separately will lead to poor sparsity of the first ranking sequence, thus verifying the effectiveness of the scheme of ranking multiple sequences simultaneously.



(a) Two parameters. (b) Three parameters.

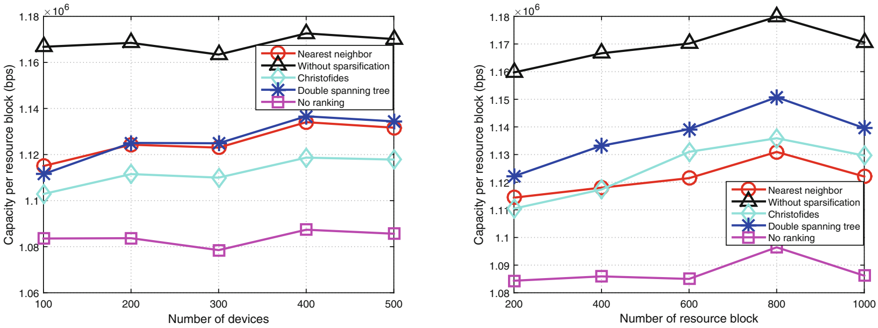
Fig. 7. Gini index.



(a) Two parameters. (b) Three parameters.

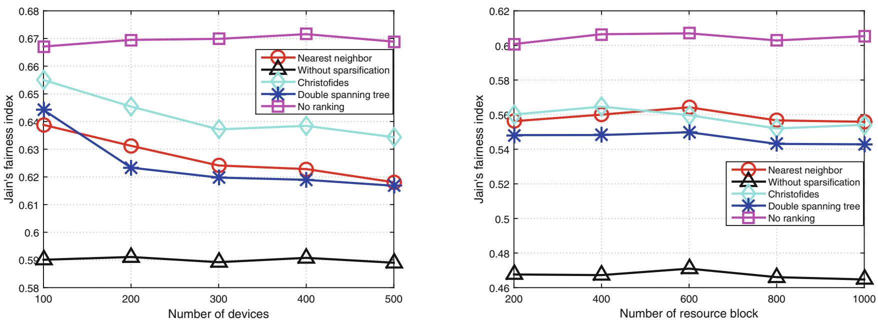
Fig. 8. Reconstruction errors.

Figure 9 and Fig. 10 show the performance improvement after applying the terminal ranking method proposed in this paper to interference coordination. It can be seen from Fig. 9 that capacity per resource block is not significantly affected by the removal of wavelet coefficients in interference coordination, which is better than directly using wavelet decomposition without ranking to reduce the problem size. It can be seen from Fig. 10 that the fairness of terminals is greatly improved due to the use of wavelet transform. However, the ranking scheme in this paper will make the fairness somewhat lower, which is lower than the method of using wavelet transform directly without ranking. By comparing the subgraphs in two figures, it is found that the sparsity of considering one parameter more makes the capacity per resource block of the network



(a) Two parameters. (b) Three parameters.

Fig. 9. Capacity per resource block.



(a) Two parameters. (b) Three parameters.

Fig. 10. Jain's fairness index.

slightly increase, and the difference of the capacity per resource block of various algorithms slightly decrease. At the same time, it is found that the sparsity of considering one parameter more will lead to a slight decrease in the fairness of terminals, and the difference of the fairness of each algorithm will also be slightly reduced.

The scheme proposed in the paper improves the sparsity of parameter matrix as much as possible by ranking terminals. Compared with no-ranking method, the randomness of terminals makes the sparsity of the original parameter matrix very poor, which results in wavelet transformation coefficients with large modulus are too many, and the scaling transformation coefficients can't approximately reflect the variation characteristics of the original parameter matrix. The result of sparse-domain interference coordination using the scaling transformation coefficients no longer corresponds to the approximate optimal coordination strategy in the original domain. Therefore, the proposed scheme is superior to the no-ranking scheme in each performance indicator. Of course, this scheme will introduce more time consuming in the process of terminal ranking. In order to ensure that the resource management process is completed within milliseconds, we will carry out terminal ranking and interference coordination respectively. As shown in Fig. 6, terminal ranking is completed before interference coordination and does not take up time in the resource management cycle. Therefore, we compare the time cost of terminal ranking and interference coordination respectively.

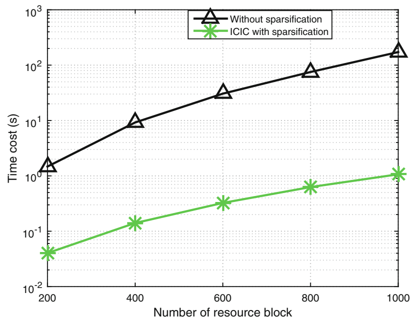


Fig. 11. Time cost of interference coordination.

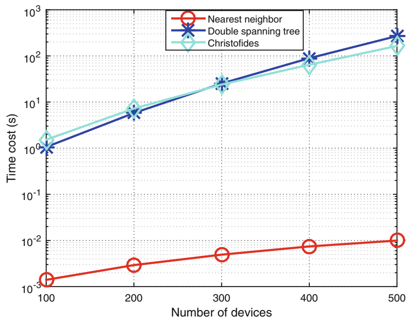


Fig. 12. Time cost of terminal ranking.

Figure 11 compares the computational time of the interference coordination optimization. As can be seen, the use of wavelet transform can significantly reduce the size of the problem, so that the time cost of interference coordination is only one percent of magnitude of the traditional scheme. As can be seen from Fig. 12, the nearest neighbor algorithm has the minimum time cost, because it only ranks according to the relative size between sequence values. When the number of terminals is small, the Christofides algorithm is more time-consuming than the double spanning tree algorithm. Because the step of minimum-weight perfect matching of the odd-degree vertexes in Christofides algorithm introduces a lot of time. But when the number of terminals is increased, the Christofides algorithm is less time-consuming than the double spanning tree algorithm. This is because the total number of edges of an Euler diagram constructed in Christofides algorithm is much less than the double spanning tree algorithm, so that it may take less time to find Eulerian cycle.

5 Conclusion

This paper studied sparsification of interference coordination parameters. On the one hand, we considered multiple characteristic parameters of the terminal to better meet the service requirements of each terminal. On the other hand, in order to reduce the computational time of scheme, a large amount of original data was sparsely represented before interference coordination. Therefore, this paper proposed a graph-based terminal ranking scheme. Terminals and its parameters corresponded to the vertexes and edge weights in the graph, respectively. And then the terminal ranking problem could be turned into finding a Hamiltonian path problem in the graph, which could be solved with the help of the correlation graph theory algorithms. Based on the proposed scheme, this paper also designed a two-period interference coordination framework with practical value. Simulation results showed that the proposed scheme could greatly reduce the computational time of interference coordination and keep the better performance in all aspects.

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