IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received September 15, 2021, accepted October 13, 2021, date of publication October 29, 2021,
date of current version November 12, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3124361

A Fast Terminal Matching Method for Interference Coordination Based on Wavelet Transform and Graph Theory in Ultra-Dense Multi-Cell Scenarios

JUNXIANG GOU[1], LUSHENG WANG[1], (Member, IEEE), HAI LIN[2], (Member, IEEE), MIN PENG[1], (Member, IEEE), AND CAIHONG KAI[1], (Member, IEEE)

[1]Key Laboratory of Knowledge Engineering with Big Data, Ministry of Education, School of Computer Science and Information Engineering, Hefei University of Technology, Hefei 230601, China
[2]Key Laboratory of Aerospace Information Security and Trusted Computing, Ministry of Education, School of Cyber Science and Engineering, Wuhan University, Wuhan 430072, China

Corresponding author: Lusheng Wang (wanglusheng@hfut.edu.cn)

This work was supported in part by the National Natural Science Foundation of China under Grant 61971176, and in part by the Fundamental Research Funds for the Central Universities of China under Grant PA2019GDQT0012 and Grant PA2020GDKC0008.

ABSTRACT The intensive deployment of cells in a wireless communication system may significantly increase the network capacity, but it may cause more complex and severe inter-cell interference. In order to effectively coordinate the interference, terminals in different cells are matched with the purpose of avoiding severe interference, called terminal matching, and a fast method is proposed in this article for multi-cell scenarios. By constructing a fully weighted graph of all the base stations with interferences as the weights, the minimum spanning tree method in graph theory is used to identify the coordination relationship among all the cells, and multiple coordination pairs can be obtained. For each coordination pair, terminal matching is modeled as a two-dimensional assignment problem between the coefficients after wavelet decomposition and Hungarian algorithm is applied to obtain their optimal match. Wavelet transform is used to extract the scale transformation coefficients describing the terminal features in each single cell, so that the optimization process can be accelerated because the amount of these coefficients is dramatically reduced after several layers of wavelet decomposition. The minimum Hamilton path method in graph theory is used to rank the terminals in each cell based on their key features, so that the coefficients lose as minimum useful information as possible during wavelet decomposition. Simulation results show that the performance of the proposed method reaches approximately the optimal matching obtained by traversing all the coordination possibilities among all the cells. Compared with the simulated annealing algorithm, the performance loss in terms of system spectral efficiency is only about 2%, but the proposed method requires only less than one thousandth of its computational time.

INDEX TERMS Ultra-dense network, interference coordination, wavelet transform, graph theory, multiple-dimensional assignment problem.

I. INTRODUCTION

With the emergence of a large number of intelligent terminal devices and all kinds of emerging applications, such as virtual reality, 3D media, and Internet of things, the network traffic explosively grows. Therefore, it will become more and more important to adopt ultra-dense network (UDN) to greatly increase the system capacity [1]. As the spectrum resources of wireless communication are very scarce, it is necessary to use frequency reuse technology to improve the network capacity and spectrum resource utilization. To make the reuse factor as 1, we hope that each cell can use all the spectrum resources, but it also causes serious inter-cell interference [2], [3]. Especially in an UDN, the intensive deployment of cells will lead to more complex inter-cell interference, which limits the system performance [4]. Therefore, in order to reduce the

The associate editor coordinating the review of this manuscript and approving it for publication was Yuan Gao.

inter-cell interference to the maximum extent, many inter-cell interference coordination techniques are used to allocate spectrum resources reasonably [5]–[7].

Interference coordination technology is to control the allocation of system resources (such as time, frequency, and power) to ensure that inter-cell interference is within an acceptable range. It is mainly divided into static and dynamic coordination schemes [8]. Static coordination is based on frequency reuse, which is realized by assigning fixed subcarrier sets and power levels to each cell and terminal in advance. They are simple and do not require frequent signaling interaction between base stations (BSs). However, this kind of method only adapts to the change of cell load by changing the spectrum and power used by different terminals, so the performance is not necessarily good because of many restrictions. Dynamic coordination allocates subcarriers and power in real time according to the terminals' features in each cell. It is especially suitable for considering all kinds of dynamic characteristics of future communication networks (such as terminal locations and traffic loads). Therefore, dynamic coordination can adapt to dynamic changes of cell load more effectively and reduce inter-cell interference.

At present, there are many researches on inter-cell interference coordination. In [9], users were divided into center users and edge users, and fractional frequency reuse was used for multi-cell frequency allocation. There are many studies using static coordination, but it is generally applicable to cell networks with regular shape. There are also some papers to use the idea of iterative solution to allocate resources. Ahmadi *et al.* [10] proposed a resource allocation scheme that combined the ant colony algorithm for subcarrier allocation and the water-filling algorithm for power allocation. By iterative comparisons among all possible solutions, the algorithm selected the one with the highest performance, so it could take too much time. Ma *et al.* [11] proposed a downlink multi-cell resource allocation scheme based on pricing. The resource allocation process was divided into sub-channel allocation and power allocation based on pricing mechanism, and the iterative water-filling algorithm was adopted to solve the optimization problem based on Karush-Kuhn-Tucker condition. Hassen *et al.* [12] proposed a distributed and coordinated resource allocation algorithm for multi-cell MIMO-OFDMA systems. Each cell divided users into edge users and center users according to a dynamic threshold value, and a resource allocation algorithm was proposed to allocate resource blocks for its center users. Virtual resource blocks were constructed by aggregating unused subcarriers of center users and allocating to edge users. Kashaf *et al.* [13] introduced a parameter for each cell to control the transmission power of the central frequency band, so as to reduce the interference of center users to edge users of the neighboring cells, and proposed a self-optimizing method of downlink inter-cell interference coordination parameters based on genetic algorithm. Zhang and Zuo [14] proposed an optimization method for uplink power control parameters based on network utility maximization, in which each cell could semi-autonomously optimize its uplink power control parameters only by exchanging several key variables through inter-cell coordination. Some papers used joint optimization to allocate resources efficiently. Qu *et al.* [15] carried out joint optimization of mobile terminal offloading and interference coordination in ultra-dense heterogeneous network, and proposed a heuristic algorithm using a step-by-step solution to improve the signal-to-noise ratio and data rate of terminals. In [16], the energy consumption and interference coordination problems in UDNs were jointly modeled as a maximum-minimum energy saving and enhanced inter-cell interference coordination problem. The goal was to maximize the energy efficiency of the worst users in the cell, and fractional programming and Lagrange dual decomposition method were used to solve the problem. In [17], the throughput maximization problem of UDNs was decoupled into two sub-problems: user clustering and sub-channel assignment. A method based on machine learning to construct conflict graph with high precision was proposed, and sub-channels were assigned to users to minimize the accumulative interference between clusters. In [18], a resource allocation algorithm based on cooperative Nash bargaining model was proposed for joint optimization of subchannel and power allocation in uplink. The algorithm considered cross-tier interference, minimum outage probability, fairness, and other factors, which obtained a Pareto-optimal equilibrium solution. In [19], the joint transmission between users was studied to improve the spectral efficiency of edge users, a dynamic coordination method was adopted to classify all the users, and an iterative algorithm was used to further optimize system performance. Pratap *et al.* [20] proposed an efficient resource allocation algorithm for 5G network, which jointly considered the goals of resource allocation, interference minimization, user-level and cell-level fairness, etc. Masouros *et al.* [21] thought interference signals could increase the useful power of the signal in a flash, and provided an undeveloped additional signal power source. Therefore, the known interference could be used to manipulate and utilize the interference beneficial to the system, so as to improve the performance. Without increasing the average transmission power of the BSs, the performance benefit could also be generated.

One obvious drawback of the traditional multi-cell interference coordination methods is that they take too long computational time hence not practical, especially in UDNs. There are some related studies that can reduce the time cost of coordination algorithm. In [22], discrete wavelet transform was used to decompose a large number of original data to get the high and low frequency components, and only a small number of low frequency coefficients were used for interference coordination. However, this method needed to ensure that the original data had good sparsity, otherwise it would cause significant performance loss. The authors' study in [23] proved that the reverse matching according to the effective signals and interferences corresponded to the optimal coordination result. Some papers reduced the

problem scale by clustering. Forouzan and Ghorashi [24] used interference graph to cluster users to minimize inter-cluster interference, and then allocated resources to clusters instead of users. Since the number of clusters was far less than the number of users, the computational time was significantly reduced. Sun *et al.* [25] proposed a cluster-based resource management method, which clustered the cells according to the distances between BSs, and clustered the users within each small cell. This method could reduce the intra-cluster interference and the computational time. In [26], a two-step graph coloring algorithm that could eliminate both inter-cell and inter-cluster interference was proposed. A graph coloring algorithm was applied to the edge of the cell to reduce inter-cell interference. Users and antennas were grouped within each cell, and the restricted coloring algorithm was used to reduce inter-cluster interference.

In recent years, the research of artificial intelligence methods in interference coordination field was increasing rapidly. In [27], beamforming, power control, and interference coordination of downlink were jointly modeled as a non-convex optimization problem that maximized the sum of signal-to-noise ratio of all the users, and deep reinforcement learning was used to solve this problem. Wang *et al.* [28] studied the problem of interference management in dense small cell networks, in which the BSs determined the downlink transmission power through autonomous perception of the surrounding interference. The problem was modeled as a partial observable Markov decision process, which was solved by multi-agent reinforcement learning method. In [29], a method of dynamically adjusting the transmission power of small BSs to adapt to the dynamic changes of network was proposed. It was modeled as a Markov decision process, and solved by the actor-critic algorithm. In addition, some researchers tried to use intelligent methods for the prediction of resource allocation. For some transmission scenarios with critical mission or delay sensitive business, the time cost of real-time optimal resource allocation is still very large. Therefore, it can allocate resources effectively in a pre-deployment way. In [30], deep neural networks were used to complete the prediction of interference coordination strategy in heterogeneous networks. A prediction window was used to learn the intermediate results of the optimal strategy. Mahmood *et al.* [31] put forward a new interference prediction algorithm based on wireless resource management. The interference change was modeled as a discrete-state-space discrete-time Markov chain, so that radio resources could be effectively configured to reduce interference. In [32], the joint design of computation offloading and interference coordination for edge intelligence empowered small cell networks was studied. a distributed multi-agent deep reinforcement learning scheme was proposed with the objective of minimizing the overall energy consumption while ensuring the latency requirements. Although the decision time of an intelligent method is usually very short, it needs a large training set and a long time of training to get a good neural network, and it also needs a large training set. Training sets in this problem are generally obtained by randomly deploying BSs and terminals, and data in the training sets do not have similar inherent characteristics. Therefore, the acquisition of training set data may become a difficulty limiting the application of such intelligent methods.

In this paper, we study a multi-cell scenario with irregular shape. Interference coordination in this scenario belongs to the multiple-dimensional assignment problem which is typically NP-hard. As the numbers of cells and terminals increase, the dimension of solution space increases exponentially. Search algorithms take a long time to iteratively solve it. For some methods like deep Q learning, it also takes a long time to train a neural network. The purpose of this paper is to propose an interference coordination scheme which consumes very little time but maintain good performance. The scheme does not need to go through a long time of repeated iteration, but only needs a limited number of cycles to get the multi-cell coordination strategy. The multi-cell coordination problem degenerates into multiple two-cell coordination problems, which corresponds to multiple two-dimensional assignment problems. Each of such problems can be directly solved by the Hungarian algorithm in polynomial time, so a fast terminal matching method integrating wavelet transform and graph theory is proposed in this paper. This integration is not just a combination of multiple mathematical methods but a quite coherent and systematic design, making it precisely suitable for the purpose of dramatically decreasing the coordination time. Firstly, the minimum spanning tree in graph theory is used to obtain multiple coordination pairs, which transforms the multi-cell coordination into multiple two-cell coordinations. Then, for each coordination pair, wavelet transform is used to reduce the computational time and sparsification method is used to reduce the useful information loss of characteristic parameters in the process of wavelet decomposition. Finally, Hungarian algorithm is used to find the optimal coordination strategy of the terminals. Simulation results show that this method can maintain good system performance and greatly reduce interference coordination time.

The rest of the paper is organized as follows. Section II describes the system model. Section III describes the proposed method. Section IV shows the performance evaluation. In the end, the paper is concluded in Section V.

II. SYSTEM MODEL FOR MULTI-CELL INTERFERENCE COORDINATION

This paper focuses on the uplink transmissions within a system consisting of $\mathcal{K}$ adjacent cells, denoted by $\mathbf{BS} = \{BS_k \,|k = 1, 2, \cdots, \mathcal{K}\}$ as the $\mathcal{K}$ BSs. Resource blocks (RBs) are denoted by $\mathbf{RB} = \{RB_n \,|n = 1, 2, \cdots, \mathcal{N}\}$, where $\mathcal{N}$ is the total amount of RBs possessed by the system. By assuming that the system is saturated with traffic flows, all the RBs are occupied for transmissions during each scheduling period. Supposing each terminal holds $\mathcal{M}$ characteristic parameters, such as useful signal power, interference power, application requirements, and power consumption, cell k can

be described by

$$\mathbf{CP}^k = \left\{ CP^k_{m,n} | m = 1, 2, \cdots \mathcal{K}, \mathcal{K}+1, \cdots, \mathcal{K}+\mathcal{M}-2; \; n = 1, 2, \cdots, \mathcal{N} \right\} \quad (1)$$

where $CP^k_{m,n}$ represents the value of the mth characteristic parameter of the terminal occupying RB n in cell k. In the following study, we put the useful signal power and interference power in the first $\mathcal{K}$ rows of this matrix. For $m = k$, the mth row represents the useful signal power to its own BS, while the other rows represent the interferences. Besides useful signal and interference, there are still $\mathcal{M} - 2$ characteristic parameters, which are put as the following $\mathcal{M}-2$ rows in the matrix.

Here, a BS may not be able to handle all the signaling in a very-short coherent interval, so the above matrix $\mathbf{CP}^k$ may not be available in time. To solve the above problem, we can deploy a macro BS (MBS) to manage all the small BSs. Because the computing power of the MBS is much greater, and the specific location of all the small BSs can be accurately known through the positioning technology, it is easy to obtain the distance between BSs and the interference signal strength and other information, so the MBS can assist each small BS to process all the signaling to obtain the corresponding parameter matrix $\mathbf{CP}^k$.

Interference coordination is to coordinate the matches between terminals within different cells, so that terminals causing severe interferences are not matched together, i.e., not using the same RBs. By fixing the indices of RBs, a coordination strategy is to find a rank of terminals in each cell, denoted by $\mathbf{A}_k = \{A_k(n) | \, n = 1, 2, \cdots, \mathcal{N}\}$ for cell k, where $A_k(n)$ represents the terminal index occupying RB n in cell k. Therefore, the performance of this terminal can be denoted by

$$S^n_k = f[\underbrace{\left(\mathbf{CP}^k, A_k(n)\right)}_{\text{(a)}}, \underbrace{\sum_{l \neq k} \left(\mathbf{CP}^l, A_l(n)\right)}_{\text{(b)}}] \quad (2)$$

where $f(\cdot)$ is a utility function correlated with $\mathcal{M}$ characteristic parameters, such as transmission rate. Expression (a) represents a certain parameter, such as the useful signal in row k of $\mathbf{CP}^k$. Expression (b) represents all the other parameters using the same RB, such as the interference from cell l in row k of $\mathbf{CP}^l$.

Since the objective of an interference coordination is to optimize a certain performance metric, the problem can be considered as a matching problem between RBs and terminals, given by

$$\mathbf{A}^*_{k,k\in\mathbf{BS}} = \underset{\mathbf{A}_{k,k\in\mathbf{BS}}}{argmax} \frac{1}{\mathcal{KN}} \sum_{k=1}^{\mathcal{K}} \sum_{n=1}^{\mathcal{N}} S^n_k \quad (3)$$

where $\mathbf{A}^*_{k,k\in\mathbf{BS}}$ represents the optimized matching result.

When $\mathcal{K} \geq 3$, the above problem is a multiple dimensional assignment problem, which is a typical NP-hard problem and unable to be solved in polynomial-time. Neither exhaustive search nor traditional optimum search, such as simulated annealing, could reach a near-optimal solution in an acceptable time period. Meanwhile, an UDN contains too many terminals, which extremely increases the solution space and the complexity of this problem. Therefore, we design a fast terminal matching method for multi-cell interference coordination in this paper, which guarantees a relatively good matching strategy in a short computational time.

Note that we have simplified the system model without taking into account issues such as signaling overhead and channel estimation. In wireless communication, frequent signaling interactions between terminals and BSs may result in a large signaling overhead, but we assume that such interactions are not required due to the following reason. When a communication link is established through signaling interaction, it is assumed that the terminal will continue to send/receive data from the BS during a period of time, and the signaling overhead during this period can be considered very small, which can be ignored in our design. In addition, resource allocation in this study is carried out in the scenario where terminal channel information is determined, so pilot assignment and channel estimation are not involved. At the same time, locations of terminals in the scenario do not change much, so there is no need to consider handover between different cells. The power allocation problem does exist, but the main consideration in this paper is the allocation of spectrum resources, so the power allocation is not the main factor to solve the interference coordination problem.

III. THE PROPOSED FAST MULTI-CELL INTERFERENCE COORDINATION METHOD

In this section, a method is proposed for fast multi-cell interference coordination with the purpose of dramatically decreasing the problem scale and the computational time. Wavelet transform is used to extract the scale transformation coefficients describing the terminal features in each single cell. Since the length of these coefficients is much smaller than that of the characteristic parameters, the problem scale is significantly decreased. To enhance the sparsification of the characteristic parameters for transformation, the minimum Hamilton cycle algorithm is used to rank the terminals in each cell. Considering that the scenario usually contains multiple cells, the multiple-cell coordination must be degenerated into multiple two-cell coordinations beforehand and the minimum spanning tree algorithm is found quite suitable for this task. Finally, for each two-cell coordination between the scale transformation coefficients, Hungarian algorithm can be applied to obtain their final matching [33]. The whole method is a coherent and systematic design, and each part is a necessary process for obtaining the final matching. The three key parts are described in the following three subsections and Subsection D is used to demonstrate the logic flow of the whole method.

A. MINIMUM SPANNING TREE METHOD FOR IDENTIFYING THE COORDINATION RELATIONSHIP AMONG ALL THE CELLS

Multi-cell interference coordination is a multi-dimensional assignment problem, which cannot be easily solved. The core concept of this paper is to separate multiple cells into multiple coordination pairs by the minimum spanning tree method, so that the problem can be transferred into a number of sub-problems of terminal matching within coordination pairs. The method contains two key steps as follows.

1) CONSTRUCTION OF THE INTERFERENCE GRAPH

An interference graph of all the cells in the scenario is constructed, given by $G' = (\mathbf{V}', \mathbf{E}')$, where the vertex set $\mathbf{V}'$ is composed of the BSs and the edge set $\mathbf{E}'$ with weights represents interferences between the BSs. The keypoint for constructing this graph is the calculation of the weights on the edges. The edge weights on the interference graph should be obtained from the physical channels, i.e., the interference signal strength of the terminals between the cells. However, since the terminals' positions or application requirements during a period of time do not change, the interference signal strength of terminals will not change significantly. By averaging them over a period of time, they tend to be a stable value and can be equivalent to the distance between BSs, so we directly take the distances between BSs as the edges' weights.

2) IDENTIFICATION OF THE COORDINATION RELATIONSHIP

Since it is difficult to solve the multi-cell coordination directly, we transfer it into multiple two-dimensional assignment problems. The idea is to coordinate the cells two-by-two from a given root which should be a cell receiving severe interferences from adjacent cells. Different methods for identifying the coordination relationship lead to different performances, but the task is to coordinate the severe interferences if they cannot be all coordinated. After an interference graph is constructed, we reverse the weights and find its minimum spanning tree. Since the edges on this tree shows the most severe inter-cell interferences and identifies the coordination relationship between them, we could form one coordination pair for each edge on the tree, so we finally obtain $\mathcal{K} - 1$ coordination pairs.

There are two classical algorithms to generate minimum spanning tree, i.e., Kruskal algorithm and Prim algorithm. They both employ the greedy concept, but the former adds the smallest edge to the tree while the latter adds the nearest node instead. For an UDN, BSs are usually quite close with one another, so the studied graph is a dense graph containing quite a lot of edges. The Kruskal algorithm requires more computational time than the Prim algorithm for this scenario, so we select the latter in the following study. During each iteration of the Prim algorithm, the newly added BS to the tree is the one not yet selected but causing the most severe interference to the selected ones, so the edges in the minimum spanning tree indicates the most severe inter-cell interferences in the scenario.

B. WAVELET DECOMPOSITION AND TERMINAL MATCHING FOR EACH COORDINATION PAIR

After the process in the above subsection, the multi-cell interference coordination problem is transferred heuristically into a number of two-cell interference coordination problems. Each two-cell coordination is a two-dimensional assignment problem by matching the terminals between the two cells, given by

$$\mathbf{A}_2^* = \underset{\mathbf{A}_2}{argmax} \frac{1}{2\mathcal{N}} \sum_{n=1}^{\mathcal{N}} S_1^n + S_2^n \tag{4}$$

where $\mathbf{A}_2^*$ is the optimal coordination strategy. S_1^n and S_2^n are the utilities of the two terminals using the nth RB in the two cells, respectively.

Here, we only consider the useful signals and interferences of cell k, then its parameter matrix can be denoted by

$$\mathbf{CP}^k = \left\{ CP_{m,n}^k \,|m = 1, 2; n = 1, 2, \cdots, \mathcal{N} \right\}, \quad k = 1, 2 \tag{5}$$

When spectral efficiency is considered as the utility, S_1^n and S_2^n can be denoted by

$$S_1^n = \log_2 \left(1 + \frac{CP_{1,n}^1}{CP_{1,A_2(n)}^2 + N_0} \right) \tag{6}$$

$$S_2^n = \log_2 \left(1 + \frac{CP_{2,A_2(n)}^2}{CP_{2,n}^1 + N_0} \right) \tag{7}$$

where N_0 represents the additive white Gaussian noise.

The problem in (4) can be solved by the traditional Hungarian algorithm, but it should be quite time consuming when the number of terminals is large. Therefore, we employ the discrete wavelet transform to process each row (a vector of terminal feature of a cell) in (5), so that the scale of the optimization correlated to the number of terminals can be significantly reduced. After several layers' wavelet decomposition, the scale transformation coefficients that contain the major information of the original vectors form new but short matrices, given by

$$\mathbf{CPS}^k = \left\{ CPS_{m,n}^k \,|m = 1, 2; n = 1, 2, \cdots, \mathcal{N}_\mathcal{S} \right\}, \quad k = 1, 2 \tag{8}$$

where $\mathcal{N}_\mathcal{S} \approx \mathcal{N}/2^\mathcal{L}$ is the length of each scale transformation coefficient vector after decomposition, and $\mathcal{L}$ is the number of layers of decomposition. Thus, the scale of the problem decreases from $\mathcal{N}$ to $\mathcal{N}_\mathcal{S}$ after the above process.

C. MINIMUM HAMILTON PATH METHOD FOR RANKING THE TERMINALS IN EACH CELL

The scale of the problem is significantly reduced by wavelet decomposition as described in the above subsection, but the retained scale transformation coefficients do not fully

represent the original matrices $\mathbf{CP}^k$, i.e., there should be a certain level of information loss during this decomposition. Since these coefficients are the low frequency components and roughly demonstrate the macroscopic trend of the curve drawn by the coefficients, it is helpful to keep this loss as minimum as possible by ranking the terminals so that the values in the parameter vectors become smooth. Considering that the $\mathcal{M}$ characteristic parameters all describe the same set of terminals, it is the rank of the terminals that decides the $\mathcal{M}$ vectors of parameters. Therefore, there must be an issue of terminal ranking in each cell to help limit the loss of information during wavelet decomposition.

This issue is modeled by graph theory in this paper. Terminals in the cell form the vertex set $\mathbf{V} = \{v_n | n = 1, 2, \cdots, \mathcal{N}_\mathcal{T}\}$, where $\mathcal{N}_\mathcal{T}$ represents the number of terminals in the cell. Edges represent the dissimilarities of terminals linked by them, denoted by $\mathbf{E} = \left\{(v_i, v_j) | i, j = 1, 2, \cdots, \mathcal{N}_\mathcal{T}, i \neq j\right\}$. When a single characteristic parameter is used, the dissimilarity is surely the difference, i.e., $CP_{m,i} - CP_{m,j}$. When multiple parameters are used, each parameter corresponds to one dimension of the space, so the Euclidean distance described by these parameters between two terminals is exactly the edge weight. Since parameters may have different units, they should be normalized beforehand. Therefore, the weights of edges can be calculated by

$$w_{i,j} = \sqrt{\sum_{m=1}^{\mathcal{M}} (\overline{CP}_{m,i} - \overline{CP}_{m,j})^2} \tag{9}$$

where $\bar{\cdot}$ represents the normalization of this parameter. After the above modeling, the terminals in a cell form an undirected graph $G = (\mathbf{V}, \mathbf{E})$, so we could employ graph theory to find a terminal ranking strategy $\mathbf{A} = \{A(n) | n = 1, 2, \cdots, \mathcal{N}_\mathcal{T}\}$ that minimizes the total dissimilarity between adjacent terminals in the rank, given by

$$\mathbf{A}^* = \underset{\mathbf{A}}{argmin} \sum_{n=1}^{\mathcal{N}_\mathcal{T}-1} w_{A(n),A(n+1)} \tag{10}$$

The solution of (10) corresponds to the minimum Hamilton path, which is a classical NP-hard problem. Our idea is to find a relatively small Hamilton cycle employing a certain recognized algorithm in graph theory, and remove the edge with the maximum weight in this cycle to obtain a Hamilton path. There are generally two types of algorithms to find a Hamilton cycle: optimum searching algorithms, such as simulated annealing and genetic algorithm, and approximation algorithms, such as nearest neighbor algorithm and double spanning tree algorithm. Optimum searching algorithms usually reach a near-optimal solution in a sufficiently long time, but their long searching time feature contradicts our intention of reducing the computation time of the whole method. In the approximation algorithms, we select the nearest neighbor algorithm in this study due to the fact that different approximation algorithms reach similar results and this algorithm usually requires less computational time than the others.

The nearest neighbor algorithm employs the greedy concept which adds the edge with the minimum weight from the unselected edges during each round, whose detailed steps are given as follows:

Step 1: Select randomly a terminal $v_1 \in \mathbf{V}$. Use $\mathbf{H}$ to store the obtained Hamilton cycle and initiate it as $\mathbf{H} = \{v_1\}$. Denote the unselected terminals as $\tilde{\mathbf{V}} = \mathbf{V} \backslash \mathbf{H}$.

Step 2: During each round for adding a new terminal to $\mathbf{H}$, select the new terminal satisfying $v_j^* = \underset{v_j \in \tilde{\mathbf{V}}}{argmin}\, w_{i,j}$. Suppose $\mathbf{H} = \{v_1 v_2 \cdots v_i\}$ before this round, it becomes $\mathbf{H} = \left\{v_1 v_2 \cdots v_i v_j^*\right\}$. Remove v_j^* from $\tilde{\mathbf{V}}$.

Step 3: If $\tilde{\mathbf{V}} = \emptyset$, the algorithm is complete and a Hamilton cycle is obtained. Otherwise, repeat *Step 2*.

Note that, the nearest neighbor algorithm may require a larger computational time than a real-time coordination method can tolerate, so terminal ranking can be processed beforehand in a much larger management period than resource allocation. This is reasonable because the terminal features usually do not vary as fast as the resource allocation period in the magnitude of milliseconds. Therefore, the computational time of terminal ranking is not taken into account of the total time cost of real-time coordination optimization by the proposed method.

D. PROCEDURE OF THE PROPOSED MULTI-CELL INTERFERENCE COORDINATION METHOD

Combining the innovative ideas in the three subsections above, we design a complete multi-cell interference coordination method, as shown by Fig. 1. The key processes in this method are further explained as follows:

(1) terminal ranking: for each cell, we use the Hamilton path method to obtain the rank of the terminals. This process is completed before all the other processes, so that it does not occupy the computational time of the real-time coordination.

(2) wavelet transform: a certain number of levels of wavelet decomposition is processed on the terminals that require coordination, so that a vector of scale transform coefficients is obtained for each cell.

(3) identification of the coordination relationship: interference graph for the scenario is constructed and its minimum spanning tree is found, where each edge on the tree denotes a coordination pair with severe inter-cell interference.

(4) terminal matching: for each coordination pair, terminal matching is modeled as a two-dimensional assignment problem between the scale transform coefficients of the two cells' terminals. Since $\mathbf{CPS}^k$ in (8) is used, the optimization becomes

$$\mathbf{A}_{\mathcal{S},2}^* = \underset{\mathbf{A}_{\mathcal{S},2}}{argmax} \frac{1}{2\mathcal{N}_\mathcal{S}} \sum_{n=1}^{\mathcal{N}_\mathcal{S}} \left[\log_2 \left(1 + \frac{CPS_{1,n}^1}{CPS_{1,A_2(n)}^2 + N_0} \right) + \log_2 \left(1 + \frac{CPS_{2,A_2(n)}^2}{CPS_{2,n}^1 + N_0} \right) \right] \tag{11}$$

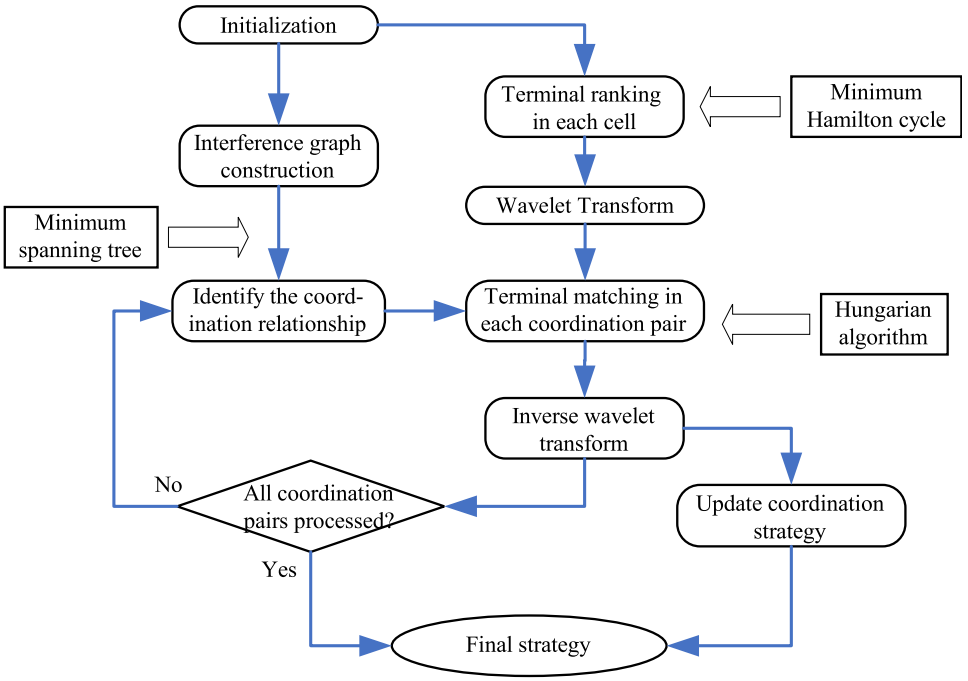


FIGURE 1. Flow chart of the proposed multi-cell interference coordination method.

Eq. (11) can also be solved by Hungarian algorithm as (4), but its computational time is significantly reduced thanks to the wavelet decomposition process.

(5) inverse wavelet transform: after Hungarian algorithm is applied on $\mathbf{CPS}^k$, the optimal matching between the scale transform coefficients is obtained as $\mathbf{A}^*_{S,2}$. This strategy should be transformed back to the matching of the terminals, so an inverse wavelet transform is applied. Although the obtained values are not exactly the same as the original characteristic parameters, their relative values still represent the rank of the terminals.

(6) update the final strategy: after the matching result for each coordination pair is obtained, the rank of terminals should be updated in the final strategy. Since the matching corresponds to the relative positions of terminals in the rank, we usually fix an initial rank for one cell and change the rank of the other cells based on the matching result.

IV. PERFORMANCE EVALUATION

In this paper, the Voronoi polygon is used to simulate the irregular shape of cells, and BSs are randomly deployed in the whole simulation area. There are a lot of terminals evenly distributed in the whole area, and each terminal is connected to the nearest BS. According to the characteristics of Voronoi polygon, all the terminals within the boundary of a cell can be regarded as terminals that can access this cell. Meanwhile, the signal transmission model adopts close-in free space path loss (CI-FSPL) model [34]. Due to the irregularity of the cells, the number of terminals accessed in each cell is inconsistent. In order to ensure that all RBs are fully used in each cell,

TABLE 1. Simulation parameters.

Parameters	Settings
Simulation area / (m · m)	100×100
Total number of terminals	10000
Bandwidth of RB /kHz	180
Transmitting power /dBm	21
Carrier frequency /GHz	3.5
Path loss formula.	CI-FSPL
White Gaussian noise power /dBm	-174
Number of RBs	100
Number of cells	3, 6, 9, 12, 15
Minimum distance between BSs /m	30, 25, 20, 15, 10

we stipulate that the number of coordinated terminals in all cells is consistent with the number of RBs in each transmission cycle. At the same time, in order to avoid the case that any two BSs are too close to each other, we also set the minimum distance between BSs. The specific parameter settings are shown in Table 1. Among them, the value of the minimum distance between BSs corresponds to the value of the number of BSs. In addition, the total number of terminals distributed in the whole area can be set arbitrarily, as long as the number of terminals accessed in each cell is no less than the number of RBs. The number of RBs set in the simulation is small, which is for the convenience of using some search algorithms (such as simulated annealing algorithm) to solve directly.

Fig. 2 shows a scenario with 9 cells. Each triangle represents a BS in a cell, each line represents the boundary of any two adjacent cells, and the dots with different colors represent the terminals associated with each BS.

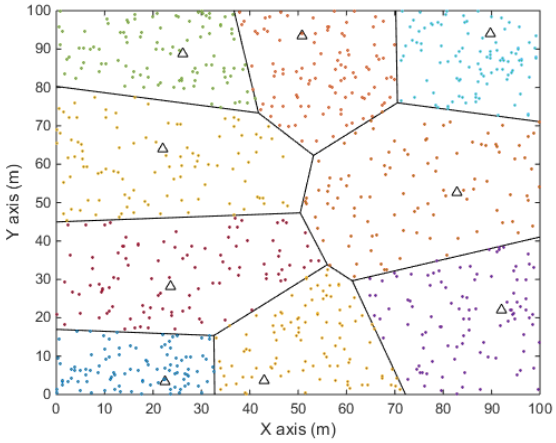


FIGURE 2. Diagram of 9-cell simulation scenario.

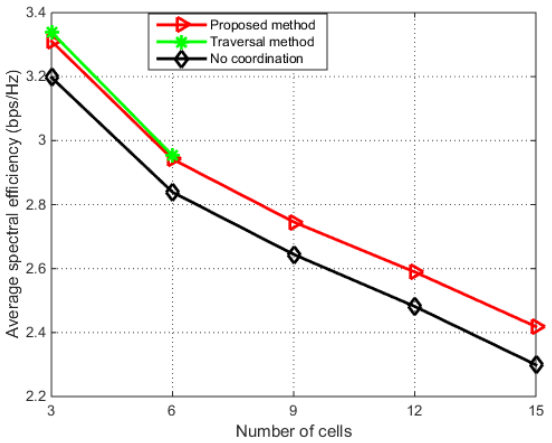


FIGURE 3. Average performance comparison of different cell matching methods.

A. PERFORMANCE VERIFICATION OF THE PROPOSED IDEAS

The proposed multi-cell interference coordination method mainly contains three innovative parts: firstly, the minimum spanning tree is used to identify the coordination relationship among all the cells; secondly, the wavelet decomposition is used to reduce the problem size; thirdly, sparsification is used to reduce the performance loss in the process of wavelet decomposition. Therefore, we show the benefits brought by the above three innovative ideas below.

1) THE INFLUENCE OF CELL MATCHING METHOD

In the proposed method, the minimum spanning tree is used to obtain multiple coordination pairs with severe inter-cell interference. From the above analysis and discussion, it can be seen that the proposed method can greatly improve the overall performance of the system by coordinating multiple coordination pairs with strong interference in the network. In order to verify how much system performance can be improved by using minimum spanning tree for identifying the coordination relationship in the proposed method, we use a traversal method for simulation comparison, i.e., all the possible coordination cases are traversed among all the cells, and the optimal coordination relationship among all the cells with the maximum performance is found in each scenario. At the same time, we set the layers of wavelet decomposition as 2 and perform sparsification.

The following is a brief introduction of the traversal method. For the cell interference graph composed of $\mathcal{K}$ cells, we use the permutation and combination idea to select $\mathcal{K}-1$ edges from the edge set of interference graph, and then judge whether these edges can form a tree. If so, its coordination relationship among all the cells will be recorded. Obviously, with the increase of $\mathcal{K}$, we can infer a total of $C_{C_{\mathcal{K}}^2}^{\mathcal{K}-1}$ possible coordination cases, so the number of coordinations among all the cells that meet the condition also increases dramatically. Because traversal method takes too long time when there are a large number of cells, we only traverse the simulation scenarios of 3 and 6 cells.

In a single scenario, the coordination relationship among all the cells obtained by using any scheme must correspond to one of the results of all traversal cases. Therefore, the performance of our proposed method must be the same as one of the performance values in the traversal method, and its performance should not be greater than the maximum. From the analysis and simulation, it is not difficult to find that the performance of the proposed method may reach the maximum value, but it has a certain relationship with the cell distribution in the whole area. In some scenarios, the performance of the proposed method may not reach the optimum, but it is still very close to it. In order to get smooth curves, we cycle the simulation process 300 times, and take the average values to compare the performance of different methods, as shown in Fig. 3.

Since the traversal method can find the optimal solution in each scenario, its average performance is the largest. The keypoint of interference coordination is to coordinate the severely interfered terminals on the edge of each cell. The proportion of these terminals is not large, so the average performance of the whole network is not significantly impacted. As shown by Fig. 3, the average spectral efficiency of the whole network only augments 3-5% from no coordination to the optimal coordination obtained by the traversal method, but this increment is already significant because the performance of some terminals on the edge has already augmented several times. The average performance of the proposed method is very close to that of the traversal method, and it is obviously greater than no coordination too. Therefore, in solving the problem of multi-cell interference coordination by using the idea of coordination pair, the proposed method using minimum spanning tree to identify the coordination relationship reaches the performance of approximately optimal matching.

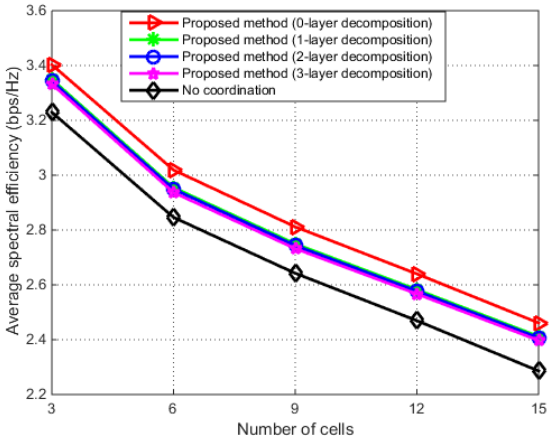


FIGURE 4. Average performance comparison of different wavelet decomposition layers.

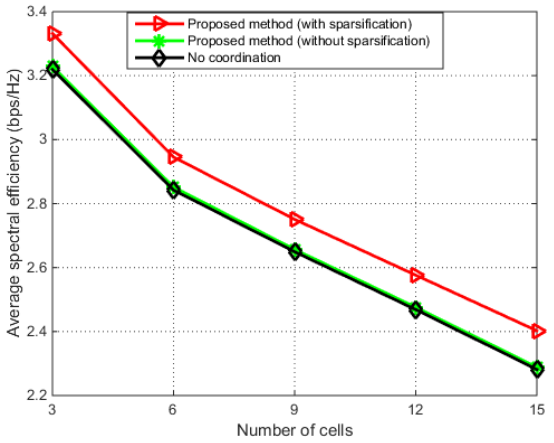


FIGURE 5. Performance comparison with and without sparsification.

2) THE INFLUENCE OF WAVELET DECOMPOSITION LAYERS

As the key step to reduce the computational time, wavelet decomposition reduces the scale of the problem, hence greatly reducing the computational time of the algorithm by compressing a large number of original feature parameter vectors. Therefore, we simulate and compare the effects of different wavelet decomposition layers on the proposed method. We set the layers of wavelet decomposition between 0 and 3. The 0-layer wavelet decomposition means that the parameter vectors are not compressed, i.e., the wavelet transform not used. In addition, we also use the minimum spanning tree for identifying the coordination relationship and sparsification for terminal ranking. The whole simulation process cycles 1000 times to take the average values, and the simulation results are shown in Fig. 4.

It can be seen that the performance of the proposed method is better than no coordination. Among the curves, the method using 0-layer wavelet decomposition (i.e., without wavelet decomposition) has the highest performance among the compared methods because it can directly obtain the optimal matching of terminals between two cells, while all the methods using wavelet decomposition both have different degrees of performance degradation. With the increase of decomposition layers, the degree of performance degradation will gradually increase. This is because the more layers of wavelet decomposition, the less effective information of the original parameter vectors can be retained after wavelet transform, so using less scale transform coefficients for interference coordination will cause more performance loss. However, we suffer the loss of system performance in exchange for a significant reduction in computational time, and the time benefit of the wavelet decomposition layers in the proposed method will be analyzed in the following simulations.

3) THE INFLUENCE OF SPARSIFICATION

In order to minimize the information loss of the parameter vectors after wavelet transform, we introduce the sparsification method to rank the terminals in the proposed method. To prove the role of sparsification method in wavelet decomposition, we compare the system performance with and without sparsification in the proposed method, that is, evaluate the performance gain of wavelet transform with sparsification. At the same time, we use the minimum spanning tree for identifying the coordination relationship and set the layers of wavelet decomposition as 2. The whole simulation process is cycled for 1000 times to take its average value, and the simulation results obtained are shown in Fig. 5.

It can be seen that the performance of the proposed method with sparsification is higher than the other two methods. The performance of the method without sparsification is very close to that of no coordination scheme. Since the redundancy of the original parameter sequences is very small, if the wavelet decomposition is carried out directly without sparsification, the retained scale coefficients cannot reflect the variation characteristics of the original parameters at all, so the performance of the method without sparsification is almost the same as that of no coordination. To sum up, the sparsity of parameters can be increased by using sparsification method, and the information loss of parameters is small after wavelet decomposition. Compared with the method without sparsification, the performance of the method with sparsification is significantly improved.

B. SIMULATION RESULTS AND ANALYSIS OF THE PROPOSED METHOD

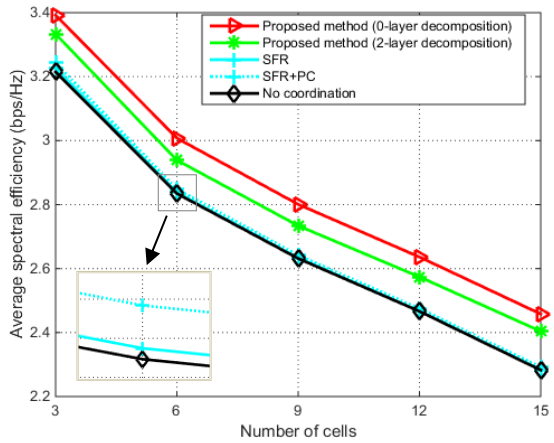
In this subsection, we compare the proposed multi-cell interference coordination method with the traditional schemes. To verify the effectiveness and robustness of the proposed method, comparisons are conducted from three perspectives, i.e., the number of cells, the transmission power, and the number of RBs. In order to effectively compare the system performance, we use simulated annealing algorithm to solve the original problem, and obtain an approximate optimal solution through a long time of iterative search. However, since the search process of the simulated annealing algorithm

is too time-consuming to draw the curve accurately in the figure, we carry out comparison and analysis of the simulated annealing algorithm separately in the end. Meanwhile, we also compare with the static scheme, i.e., soft frequency reuse (SFR).

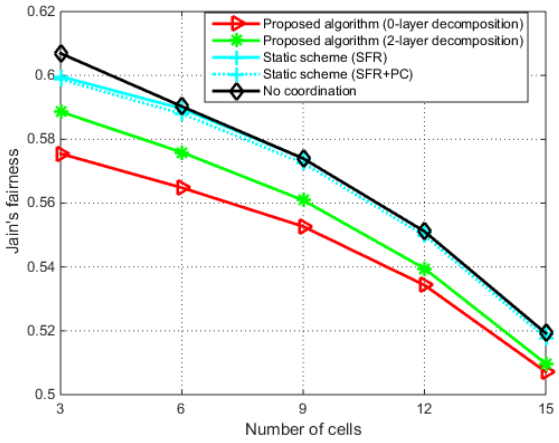
Here we briefly explain the static scheme used in the simulation. Because of the irregularity of the cells, we cannot distinguish between central users and edge users accurately by defining the boundaries. Therefore, we divide the terminals according to the distance between the terminals and its BS. In each cell, we select the part of the terminals which are farthest from the BS as the edge users, and other users as the central users. Then the spectrum resources are reused by SFR between cells. To be specific, edge users in each cell reuse the spectrum resources of central users in all the other cells, and edge users in all the cells use orthogonal spectrum resources between each other. On the basis of SFR, we also combine power control (PC) to further reduce inter-cell interference. By controlling the transmission power ratio of central users to edge users in each cell [35], the interference of central users to the neighboring cell edge users is reduced, so as to improve the spectral efficiency of the edge users and the overall performance of the system.

Fig. 6, Fig. 7, and Fig. 8 show the simulation results corresponding to the number of cells, the transmission power, and the number of RBs, respectively. From these figures, it can be concluded that the average spectral efficiency of SFR is only slightly better than that of no coordination due to the irregular shape of the cells. The average spectral efficiency of SFR + PC increases slightly, due to the ability of the appropriate control of central users to effectively reduce the inter-cell interference and thus improve the system performance to some extent. The average spectral efficiency of the proposed method is better than that of the other algorithms. The performance of the method without wavelet transform is the highest among all the compared methods, while the performance of the method with wavelet transform is slightly reduced. In addition, no coordination realizes random allocation of resources, so its Jain's fairness is high. By dividing the users into different central and edge bands, the fairness of SFR is slightly lower than that of no coordination. SFR + PC further improves the average spectral efficiency by controlling the transmission power of central users, so its fairness is lower than that of SFR and no coordination. The fairness of the proposed method is worse than that of the other algorithms. The method with wavelet transform causes performance loss but has better fairness, while the method without wavelet transform has lower fairness because it must allocate spectrum resources to edge users with poor performance.

Fig. 6 shows the system performance of each scheme corresponding to different numbers of cells. With the increase of the number of cells, interference becomes more serious and complex, so the system average spectrum efficiency and Jain's fairness of each scheme are declining. We also find that the increase of the number of cells leads to the increase of the interference, but the average spectral efficiency gap of



(a) Average spectral efficiency



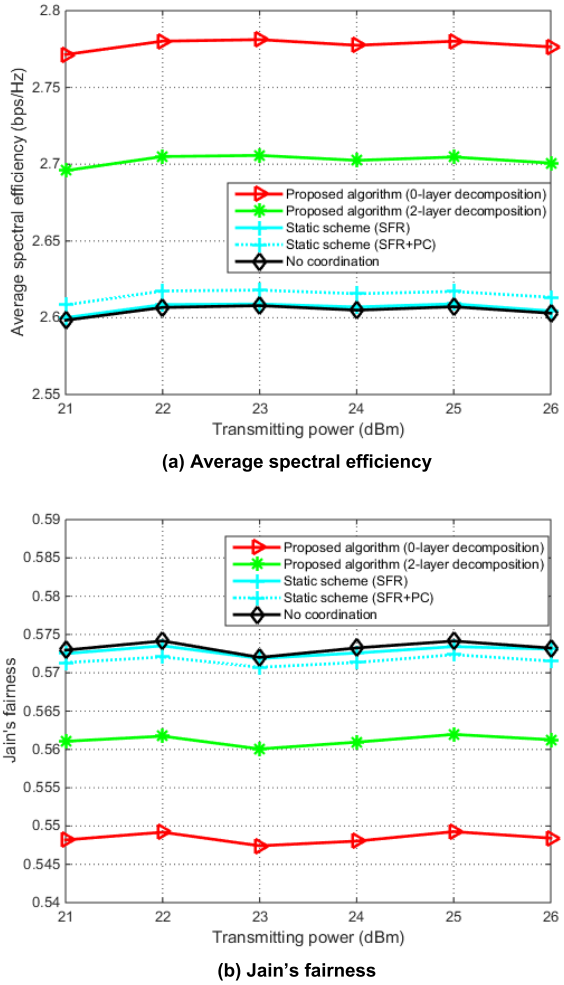
(b) Jain's fairness

FIGURE 6. System performance comparison with different numbers of cells.

each method almost remains the same. In addition, with the increase of the number of cells, the fairness gap between the curves of 0-layer and 2-layer decomposition decreases, and the gap between SFR and no coordination also decreases.

Fig. 7 shows the system performance of each scheme corresponding to different transmission power values. With the increase of transmission power, the average spectral efficiency and fairness of each algorithm almost remain unchanged. This is because the increase of transmission power increases the value of characteristic parameters such as the useful signal power of the terminals, but the average signal-to-interference-plus-noise ratio (SINR) does not increase significantly, so the system performance almost remains unchanged.

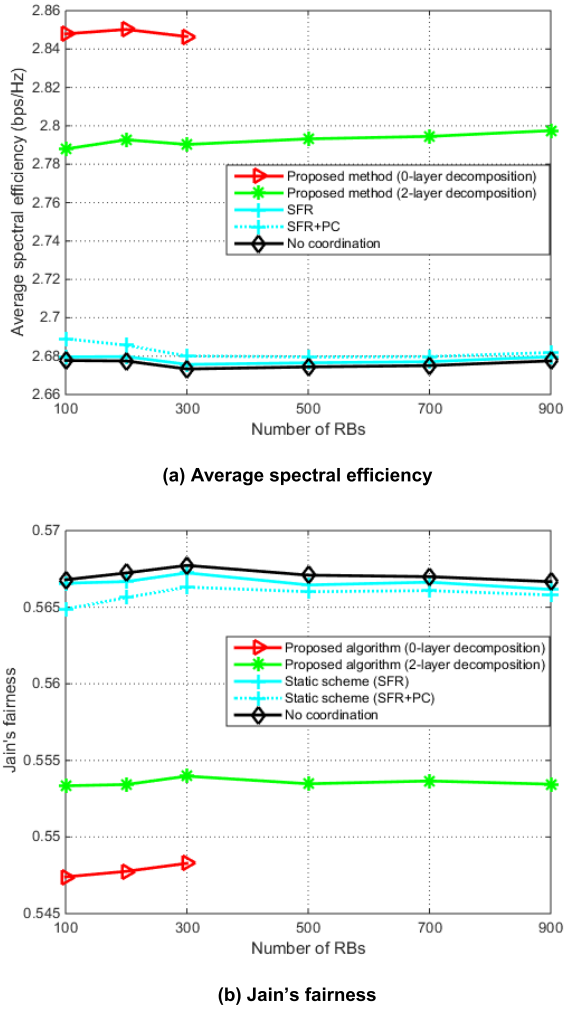
Fig. 8 shows the system performance of each scheme corresponding to different numbers of RBs. With the increase of the number of RBs, the average spectral efficiency and fairness of each algorithm are almost constant. This is because the increase of the number of RBs only increases the scale



(a) Average spectral efficiency

(b) Jain's fairness

FIGURE 7. System performance comparison with different transmitting power values.



(a) Average spectral efficiency

(b) Jain's fairness

FIGURE 8. System performance comparison with different numbers of RBs.

of the problem, but does not increase the average degree of interference between the cells. Based on Fig. 6, Fig. 7, and Fig. 8, we can also draw a conclusion that the number of cells affects the performance of the proposed method, while the transmission power and the number of RBs do not have a significant impact on the performance of the proposed method.

Computational time has always been an important metric in wireless mobile communications. In order to verify the feasibility of the proposed method, we make a comparison in the aspect of time cost. The purpose of the proposed method is to transform the original multiple dimensional assignment problem into a group of two-dimensional assignment problems by identifying the coordination relationship among all the cells, so its computational time is directly related to the number of cells. Although the number of terminals in each cell will affect the computational time of solving a two-dimensional assignment problem, it can be greatly reduced by wavelet transformation. Therefore, we compare the effect of the number of cells on computational time.

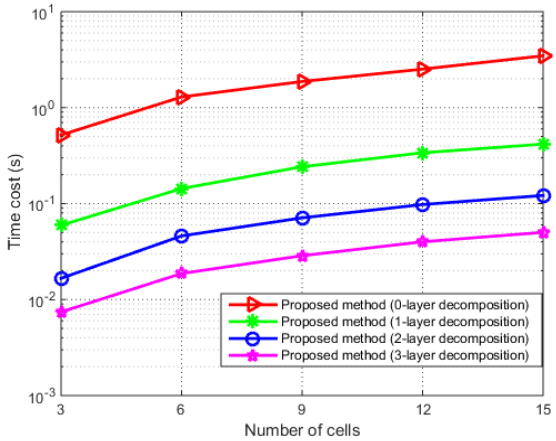


FIGURE 9. Time cost comparison among various layers of decomposition.

Fig. 9 shows that, as the number of cells increases, the time of the proposed method also increases, and the growing trend is consistent. In addition, with the increase of the number

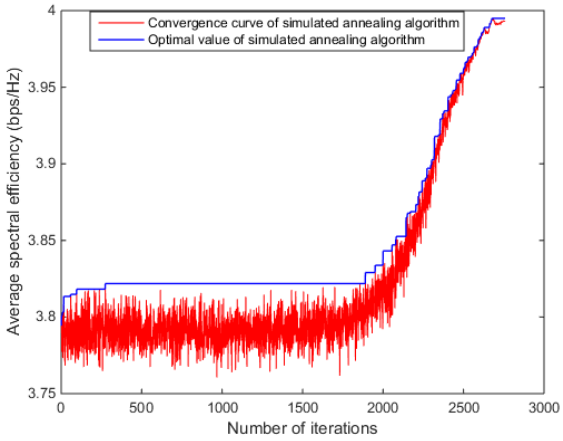


FIGURE 10. Performance convergence of simulated annealing.

of wavelet decomposition layers, the length of the feature vector is reduced, so the computational time of the methods will be reduced by a power function. According to the performance curve in Fig. 4 and the time cost curve in Fig. 9, we can roughly estimate a suitable wavelet decomposition layer. In general, when there are more terminals in each cell, we adopt more layers of wavelet decomposition, so that the time cost can be greatly reduced when cells and terminals are both massive.

C. PERFORMANCE COMPARISON BETWEEN SIMULATED ANNEALING ALGORITHM AND THE PROPOSED METHOD

Because the search time of the simulated annealing algorithm is too long, it cannot go through countless cycles to get a smooth curve similar to the above simulation figures, so we simulate this algorithm alone here, and summarize the advantages of the proposed method through comparison. We use the simulated annealing algorithm to solve a three-cell scenario directly, and get the convergence of the curve with the increase of the number of iterations as shown in Fig. 10. The convergence curve of this algorithm represents the corresponding system performance under the current number of iterations, and the optimal value curve of the simulated annealing algorithm represents the maximum performance of the system obtained by the current number of iterations, and it is obvious that the optimal value curve is non-decreasing.

When the number of iterations reaches around 2700, the growing trend of the convergence curve slows down obviously, and the optimal value curve remains basically unchanged. This indicates that the algorithm has found an approximate optimal solution of the original problem. Finally, 100 scenarios are randomly generated for simulation and the average performance of each method is taken for comparison, and the numerical results are shown in Table 2.

It can be concluded that the achieved system spectral efficiency of the simulated annealing algorithm is better than that of the proposed method, but its time cost is much larger. At the same time, the performance using 1-layer wavelet decomposition will be further reduced, as well as the time cost. The performance loss ratio of the proposed method without wavelet transform is about 1.8%, while that with 1-layer wavelet transform will increase to 3.3%. For time cost, the time ratio of the proposed method without wavelet transform is 0.063%, while that with 1-layer wavelet transform is reduced to 0.0084% of simulated annealing. In addition, we can also find that the time cost ratio with and without wavelet transform is about 8 times, which exactly meets the law that the length of the feature vector using wavelet transform is almost halved and the computational time of the Hungarian algorithm is reduced by about 1/8.

TABLE 2. Performance comparison between simulated annealing and the proposed method.

	Simulated annealing	Proposed (0-layer)	Proposed (1-layer)
System performance	3.4978	3.4332	3.3803
Time cost	769.0274	0.4822	0.0647
Performance loss ratio	/	1.85%	3.36%
Time cost ratio	/	0.063%	0.0084%

V. CONCLUSION

In the future, cells and terminals will show high density characteristics, which will lead to more complex inter-cell interference. However, traditional interference coordination schemes cannot meet the low delay demand of future mobile communication due to their huge computational time. Therefore, the main purpose of this paper is to effectively coordinate the interference between multiple cells in a short time, and a fast terminal matching method for interference coordination based on wavelet transform and graph theory is proposed. Firstly, the minimum spanning tree is used to identify the coordination relationship among all the cells, Then, each coordination pair is modeled as a two-dimensional assignment problem, and wavelet transform is used to compress the feature vectors, and then Hungarian algorithm is used to get the optimal matching of terminals. At the same time, in order to reduce the performance loss caused by wavelet decomposition, the minimum Hamilton path is used to rank the terminals to increase the sparsity of feature vectors in advance. The simulation results show that the performance of using minimum spanning tree for identifying the coordination relationship is approximately optimal among all possible coordination cases, and the proposed method can greatly reduce the computational time of interference coordination and maintain good system performance. In the future work, we will focus on the scenarios of heterogeneous cell networks, which will not only involve interference coordination but also complex cell association.

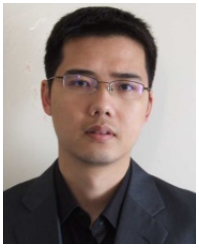
REFERENCES

[1] S. Andreev, V. Petrov, M. Dohler, and H. Yanikomeroglu, "Future of ultra-dense networks beyond 5G: Harnessing heterogeneous moving cells," *IEEE Commun. Mag.*, vol. 57, no. 6, pp. 86–92, May 2019.

[2] A. Asadi, V. Sciancalepore, and V. Mancuso, "On the efficient utilization of radio resources in extremely dense wireless networks," *IEEE Commun. Mag.*, vol. 53, no. 1, pp. 126–132, Jan. 2015.
[3] H. Zhang, S. Chen, X. Li, H. Ji, and X. Du, "Interference management for heterogeneous networks with spectral efficiency improvement," *IEEE Wireless Commun.*, vol. 22, no. 2, pp. 101–107, Apr. 2015.
[4] M. Kamel, W. Hamouda, and A. Youssef, "Ultra-dense networks: A survey," *IEEE Commun. Surveys Tuts.*, vol. 18, no. 4, pp. 2522–2545, 4th Quart., 2016.
[5] B. Soret, K. I. Pedersen, N. T. K. Jørgensen, and V. Fernández-López, "Interference coordination for dense wireless networks," *IEEE Commun. Mag.*, vol. 53, no. 1, pp. 102–109, Jan. 2015.
[6] V. Fernández-López, K. I. Pedersen, B. Soret, J. Steiner, and P. Mogensen, "Improving dense network performance through centralized scheduling and interference coordination," *IEEE Trans. Veh. Technol.*, vol. 66, no. 5, pp. 4371–4382, May 2017.
[7] K. Guo, T. Liu, C. Yang, and Z. Xiong, "Interference coordination and resource allocation planning with predicted average channel gains for HetNets," *IEEE Access*, vol. 6, pp. 60137–60151, 2018.
[8] A. S. Hamza, S. S. Khalifa, H. S. Hamza, and K. Elsayed, "A survey on inter-cell interference coordination techniques in OFDMA-based cellular networks," *IEEE Commun. Surveys Tuts.*, vol. 15, no. 4, pp. 1642–1670, 4th Quart., 2013.
[9] A. M. Saleh, N. T. Le, and A. B. Sesay, "Inter-cell interference coordination using fractional frequency reuse scheme in multi-relay multi-cell OFDMA systems," in *Proc. IEEE Can. Conf. Electr. Comput. Eng. (CCECE)*, May 2018, pp. 1–5.
[10] H. Ahmadi, Y. H. Chew, and C. C. Chai, "Multicell multiuser OFDMA dynamic resource allocation using ant colony optimization," in *Proc. IEEE 73rd Veh. Technol. Conf. (VTC Spring)*, May 2011, pp. 1–5.
[11] W. Ma, W. Zheng, H. Zhang, X. Wen, Z. Lu, and D. Liu, "Pricing-based resource allocation in downlink multi-cell OFDMA networks," in *Proc. IEEE INC, ICCIS ICMIC*, Gyeongju, South Korea, Aug. 2012, pp. 260–263.
[12] W. B. Hassen, M. Afif, and S. Tabbane, "Interference mitigation through inter-cell interference coordination using virtual PRB allocation in 4G networks," *Wireless Pers. Commun.*, vol. 90, no. 3, pp. 1179–1209, Oct. 2016.
[13] A. Kashaf, M. I. Tiwana, I. Usman, and M. I. Tiwana, "Self-organizing inter-cell interference coordination in 4G and beyond networks using genetic algorithms," *Automatika*, vol. 58, no. 1, pp. 48–54, Jan. 2017.
[14] H. Zhang and J. Zuo, "Optimization of uplink power control parameters in wireless cellular networks," in *Proc. IEEE ICCCS*, Shanghai, China, May 2020, pp. 738–741.
[15] D. Qu, S. Xie, B. Sun, and Y. ZhOU, "Joint MS offloading and interference coordination for heterogeneous ultra dense networks," in *Proc. 11th Int. Conf. Wireless Commun. Signal Process. (WCSP)*, Oct. 2019, pp. 1–6.
[16] J. Zheng, L. Gao, H. Zhang, D. Zhu, H. Wang, Q. Gao, and V. C. M. Leung, "Joint energy management and interference coordination with max-min fairness in ultra-dense HetNets," *IEEE Access*, vol. 6, pp. 32588–32600, 2018.
[17] J. Cao, T. Peng, X. Liu, W. Dong, R. Duan, Y. Yuan, W. Wang, and S. Cui, "Resource allocation for ultradense networks with machine-learning-based interference graph construction," *IEEE Internet Things J.*, vol. 7, no. 3, pp. 2137–2151, Mar. 2020.
[18] H. Zhang, C. Jiang, N. C. Beaulieu, X. Chu, X. Wang, and T. Q. S. Quek, "Resource allocation for cognitive small cell networks: A cooperative bargaining game theoretic approach," *IEEE Trans. Wireless Commun.*, vol. 14, no. 6, pp. 3481–3493, Jun. 2015.
[19] X. Li, Z. Wang, Q. Cheng, J. Fu, and S. Zhang, "Dynamic interference coordination scheme based on the iterative joint transmission in ultra dense network," *J. Commun.*, vol. 41, no. 2, pp. 176–186, Feb. 2020.
[20] A. Pratap, R. Misra, and S. K. Das, "Maximizing fairness for resource allocation in heterogeneous 5G networks," *IEEE Trans. Mobile Comput.*, vol. 20, no. 2, pp. 603–619, Feb. 2021.
[21] C. Masouros, T. Ratnarajah, M. Sellathurai, C. Papadias, and A. Shukla, "Known interference in the cellular downlink: A performance limiting factor or a source of green signal power?" *IEEE Commun. Mag.*, vol. 51, no. 10, pp. 162–171, Oct. 2013.
[22] S. Zhang, L. Wang, C. Kai, and W. Wang, "Sparse-domain interference coordination scheme in ultra-dense networks," in *Proc. IEEE 4th Int. Conf. Comput. Commun. (ICCC)*, Dec. 2018, pp. 1119–1123.
[23] Z. Zha, L. Wang, C. Huang, and C. Kai, "Quick matching for interference coordination in ultra-dense networks," *IEEE Wireless Commun. Lett.*, vol. 9, no. 1, pp. 47–50, Jan. 2020.
[24] N. Forouzan and S. A. Ghorashi, "Inter-cell interference coordination in downlink orthogonal frequency division multiple access systems using Hungarian method," *IET Commun.*, vol. 7, no. 1, pp. 23–31, Jan. 2013.
[25] Y. Sun, G. Guo, S. Zhang, S. Xu, T. Wang, and Y. Wu, "A cluster-based energy-efficient resource management scheme with QoS requirement for ultra-dense networks," *IEEE Access*, vol. 8, pp. 182412–182421, 2020.
[26] C. Ge, S. Xia, Q. Chen, and F. Adachi, "2-step graph coloring algorithm for cluster-wise distributed MU-MIMO in ultra-dense RAN," in *Proc. 23rd Int. Symp. Wireless Pers. Multimedia Commun. (WPMC)*, Oct. 2020, pp. 1–6.
[27] F. B. Mismar, B. L. Evans, and A. Alkhateeb, "Deep reinforcement learning for 5G networks: Joint beamforming, power control, and interference coordination," *IEEE Trans. Commun.*, vol. 68, no. 3, pp. 1581–1592, Mar. 2020.
[28] Y. Wang, G. Feng, Y. Sun, S. Qin, and Y.-C. Liang, "Decentralized learning based indoor interference mitigation for 5G-and-beyond systems," *IEEE Trans. Veh. Technol.*, vol. 69, no. 10, pp. 12124–12135, Oct. 2020.
[29] S. Qin, X. Dong, and G. Feng, "Intelligent interference coordination algorithm in ultra dense cellular networks," *ZTE Technol. J.*, vol. 26, no. 5, pp. 45–52, Oct. 2020.
[30] Z. Xu, J. Guo, and C. Yang, "Predictive resource allocation with interference coordination by deep learning," in *Proc. 11th Int. Conf. Wireless Commun. Signal Process. (WCSP)*, Oct. 2019, pp. 1–6.
[31] N. H. Mahmood, O. A. Lopez, H. Alves, and M. Latva-Aho, "A predictive interference management algorithm for URLLC in beyond 5G networks," *IEEE Commun. Lett.*, vol. 25, no. 3, pp. 995–999, Mar. 2021.
[32] X. Huang, S. Leng, S. Maharjan, and Y. Zhang, "Multi-agent deep reinforcement learning for computation offloading and interference coordination in small cell networks," *IEEE Trans. Veh. Technol.*, vol. 70, no. 9, pp. 9282–9293, Sep. 2021.
[33] D.-N. Vu, N.-N. Dao, and S. Cho, "Downlink sum-rate optimization leveraging Hungarian method in fog radio access networks," in *Proc. Int. Conf. Inf. Netw. (ICOIN)*, Jan. 2018, pp. 56–60.
[34] Special Interest Group (SIG) on 5G Channel Model. (Jul. 25, 2017). *5G Channel Model for Bands up to 100 GHz.* [Online]. Available: http://www.5gworkshops.com/5GCM.html.
[35] M. I. Tiwana, B. Sayrac, and Z. Altman, "Statistical learning in automated troubleshooting: Application to LTE interference mitigation," *IEEE Trans. Veh. Technol.*, vol. 59, no. 7, pp. 3651–3656, Sep. 2010.

JUNXIANG GOU was born in Guangyuan, Sichuan, China, in 1996. He received the B.E. degree in electronic information science and technology from the Beijing University of Posts and Telecommunications (BUPT), Beijing, China, in 2018. He is currently pursuing the master's degree with the Department of Communications Engineering, Hefei University of Technology (HFUT), Hefei, China. His research interest includes interference coordination in ultra-dense and heterogeneous networks.

LUSHENG WANG (Member, IEEE) received the B.Sc. degree in communications engineering from the Beijing University of Posts and Telecommunications (BUPT), China, in 2004, and the Ph.D. degree in computer science and networks from Telecom ParisTech (ENST), France, in 2010. He held a postdoctoral position with INSA-Lyon, in 2010, and Eurecom, France, from 2011 to 2012. He is currently a Research Professor and the Vice Dean of the Department of Communications Engineering, Hefei University of Technology (HFUT), China. His research interests include resource and interference management in hyper-dense and heterogeneous networks, and task offloading and resource allocation for auto-pilot vehicles and robots.



HAI LIN (Member, IEEE) received the B.S. degree from the Department of Thermal Engineering, Huazhong University of Science and Technology, Wuhan, China, in 1999, the M.S. degree in computer science from the University of Pierre and Marie Curie, Paris, France, in 2005, and the Ph.D. degree from the Institute Telecom–Telecom ParisTech, Paris, in 2008. He held a Postdoctoral Researcher position with France Telecom. He was a Researcher with ZTE Europe. Since 2012, he has been with Wuhan University, Wuhan, where he is currently an Associate Professor with the School of Cyber Science and Engineering. His research interests include the Internet of Things, network mobility, sensor networks, and future networks.

MIN PENG (Member, IEEE) received the B.S. and Ph.D. degrees from the Department of Electronic Engineering and Information Science, University of Science and Technology of China, Hefei, China, in 2005 and 2010, respectively. From 2011 to 2013, he was a Research Engineer with the Huawei Nanjing Research Institute, Nanjing. In 2013, he joined the Department of Communication Engineering, Hefei University of Technology, Hefei. His research interests include delay-tolerant networks, wireless communication, indoor positioning, and sensor networks.

CAIHONG KAI (Member, IEEE) received the B.S. degree from the Hefei University of Technology, Hefei, China, in 2003, the M.S. degree in electronic engineering and computer science from the University of Science and Technology of China, Hefei, in 2006, and the Ph.D. degree in information engineering from The Chinese University of Hong Kong, Hong Kong, China, in 2010. She is currently a Professor with the School of Computer Science and Information Engineering, Hefei University of Technology. Her research interests include wireless communication and networking, network protocols, and performance evaluation.