Coverage and Capacity Optimization Based on Tabu Search in Ultra-Dense Network

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Abstract. To meet the requirements of high system capacity and coverage of 5G network, ultra-dense network is viewed as the key technology for networking evolution. And for densely deployed small cell network, self-optimization is crucial in the aspect of reducing the cost of network management while optimizing the network performance. This paper focuses on the coverage and capacity optimization, proposing a mathematical combined optimization function to balance the conflicting key performance indicators. And under this model, we propose the tabu search algorithm for generating new antenna transmit power to optimize the performance. Simulation results show that our proposed algorithm gets significant improvement in network performance and outperforms the adaptive simulated annealing in convergence speed while optimizing.

Keywords: Ultra-dense network · Coverage and capacity optimization · Tabu search · Small cell

1 Introduction

The explosive growth of mobile data traffic these years puts forward high requirements for the bandwidth and performance of coverage and capacity of the 5th generation (5G) networks, such as ultra-high traffic volume density and ultra-high peak data rate [1]. This makes the traditional way of covering just by macro base station (MBS) difficult to meet the users' needs nowadays. Besides, large amount of data traffic occurs in some hot-spot areas, such as the office building, dense residential area, subway and other apartment, meanwhile, the data traffic is also unevenly distributed, thus causing not ideal signals and congestion in part of the network. Therefore, the ultra-dense deployment of short-distance, low-power small cell base stations become an effective solution for the challenges. Ultra-dense network (UDN) is viewed as one of the key technologies for 5G [2]. The densely deployed small cells can bring hundreds of times capacity improvement in extreme cases [1], as well as enhancement in coverage, thereby increasing the capacity of the entire network. In particular, for both indoor and outdoor high-density services requiring areas, the dense deployment of small cell base stations can effectively improve the quality of service (QoS) and provide more efficient services [3]. However, the expected large number of small

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cells as well as their much more dynamic unplanned deployment raises a variety of challenges in the area of network management [4]. To improve the network performance, automate the optimization of the network, simplify the network designing and reduce operation cost of the network, the network should be more intelligent to improve itself when needing. As one of the self-organized functions, self-optimization of the network can replace manually operations, thus reducing the cost of network management while optimizing the network performance. Through monitoring changes of performance indexes and fault events during the network operation, self-optimization can automatically select certain optimization algorithm to adjust corresponding parameters of the network, so as to achieve optimal system performance.

The coverage and capacity optimization (CCO) is based on the identification of the coverage and capacity issues and select an optimization algorithm to automatically modify parameters, to repair and improve the coverage and capacity problems. Most of the contributions consider the antenna downtilt as the parameter to be modified in LTE networks [5], while in ultra-dense network, the small cell base stations' antennas are omnidirectional and isotropic, hence we choose other parameters like transmit power to modify. Most of the existing work concentrates on combined optimization. [6] constructed an objective function to jointly maximize throughput and coverage, using a probability distribution function (PDF) for throughput measurements and an estimate of the number of covered and uncovered users of each considered cell. [7] proposed a general concept for the self-organization of multiple KPIs rather than only an algorithm for tilt-based CCO. And they proposed an effective tilt-based algorithm which combined to optimize coverage and capacity in downlink (DL) and uplink (UL) jointly. What's more, it used a real-world urban LTE deployment scenario in practice and outperformed well. [8] used the concept of effective capacity as the optimization objective, which involved the index of coverage in function, thus achieving joint optimization. When facing high complexity optimizing scenario, [9] introduced a low-complexity interference approximation model and formulated the optimization problem as a mixed-integer linear program. They proposed a traffic-light-related approach to consider multi-parameter optimization. [10] only modified a limited set of basic beams combined with an overall beam, to reduce complexity caused by 2-dimensional antenna arrays, while achieving adequate performance gains by Nelder-Mead and Q-learning approach. However, that paper mainly optimized coverage in its cost function instead of its so-called CCO. In this paper, we focus on optimize coverage and capacity in UDN, and propose a tabu search (TS) algorithm for adjusting parameters and reduce complexity under our proposed combined mathematical model.

The remainder of the paper is organized as follows. In Sect. 2, the system model and our defined mathematical model for combined optimization is introduced. In Sect. 3, we present our proposed TS algorithm and describe details applying in our ultra-dense small cell network. Simulation environment and results of CCO performance are presented and contrast with the Simulated Annealing (SA) approach in Sect. 4, and Sect. 5 concludes this paper.

2 System Model

We consider a scenario case based on a hexagonal 19-site network deployment, which has original one site deployed in the middle and other six ones wraparound it symmetrically, also with other twelve ones attached to these six ones' sides. These are 19 macro base stations, each with three sectors deployed as hexagon. The path loss between users and their serving base stations is defined by the distance between them, including propagation loss, shadow fading and antenna gain. It can be affected by many configuration parameters, including transmit power. In our work, we adjust the transmit power of the small cells with other parameters fixed, to optimize coverage and capacity in the network.

Consider a 19-site network consisting of K MBSs, M SBSs and N deployed UEs. MBSs are indexed as l, $l = 1, 2, \cdots, K$, SBSs are indexed as j, $j = 1, 2, \cdots, M$, while UEs are indexed as i, $i = 1, 2, \cdots, N$. The transmit power of all the SBSs is denoted by the vector $\mathbf{p}$, $\mathbf{p} = \{p_1, p_2, \cdots, p_M\}$. In the downlink, the transmission channel gain between SBS j and the UE i is expressed as g_{ij}, thus the received signal strength at UE i from SBS j is defined as follows:

$$P_{rx}(i,j) = p_j g_{ij} \tag{1}$$

Assume that the system noise is σ^2, hence the downlink SINR of UE i associated with SBS j is calculated as:

$$SINR_i = \frac{g_{ij} p_j}{\sigma^2 + \sum\limits_{k \neq j} g_{ik} p_k} \tag{2}$$

Then we use a function to map each user's $SINR$ to its spectal efficiency, shown in the form of a step function with each step a linear function.

$$SE_i = Map(SINR_i) \tag{3}$$

The performance of coverage and capacity can be judged by a measurement of spectral efficiency, that is, using average spectral efficiency to represent coverage and edge spectral efficiency for capacity. Hence, we use a combined optimization function to judge the performance of coverage and capacity of the overall system. The function can balance coverage and capacity optimization objectives, by using a compromise coefficient γ, $0 < \gamma < 1$. The combined optimization function is defined as follows:

$$F(\mathbf{p}) = (1-\gamma) SE_{ave} + \gamma SE_{edge} \tag{4}$$

where SE_{ave} is the average spectral efficiency which can be obtained by calculating the mean of all UEs' spectral efficiency, while SE_{edge} stands for the edge spectral efficiency which can be obtained by calculating the 5% -tile of the UEs' spectral efficiency. The typical value γ can take is 0.5, and a bigger value means we choose to pay more attention to improving the coverage performance, otherwise, to improving the capacity performance.

3 Optimization Schemes Based on Tabu Search

In order to optimize the combined function shown in 4, we use the improved tabu search algorithm to iteratively update the transmit power of SBSs. Tabu search are more used to solve combinatorial optimization problems, especially when the dimension of the problem is really high and with large amount of data. It can reduce the complexity when finding the optimal solution. The main idea of TS is to mark some local optimal solutions and try to avoid (but not completely prohibit) them, so as to avoid falling into local optima.

The TS algorithm begins with an initial solution vector, which in our work is the initial transmit power of all SBSs. However, in our work, the number of SBSs comes to 152, which means each macro cell has two small cell clusters and four SBSs in each cluster. What's more, to find a more optimal solution vector, TS defines a neighborhood around its last iteration's solution vector. In view of the transmit power of each SBS is in the range of $[-10\,\text{dBm}, 24\,\text{dBm}]$, we may have a large amount of neighborhood vectors to deal with. In order to avoid high complexity caused by the two aspects described above when calculating, instead of dealing with all the transmit power in one small iteration, we choose to view the SBSs in the same macro cell as a group. And in each inner iteration we just change one group's transmit power, to make the power vector move to the best vector among this group's neighboring vectors. The inner iteration continued until all the 19 groups' transmit power vectors have been changed to a best solution in their neighboring vectors. After finished one outer iteration, which means all SBSs' transmit power has moved to a best solution in their neighboring vectors, TS algorithm continues next outer iteration. As for the specific method to choose the best vector among neighboring vectors, definitions of related concepts should be given first. Firstly, the "neighboring vector" are the vectors that only have one element different from all the elements of the given vector. The difference aforementioned is constrained by "neighbor range", which means that the difference between the changed element and the one in the given vector must be no more than neighbor range. The TS algorithm attempts to avoid local optima by marking the newly gotten solution vectors of the past few iterations as "tabu". The number of the past few iterations is called "tabu period", set as P, which means if a solution vector is marked as tabu in an iteration, it will remain as tabu in tabu matrix for P outer iterations. The marking "tabu" is stored in "tabu matrix", whose entries corresponding to certain solution vectors are non-negative integers. These integers are updated in each outer iteration, that is, usually begin with P and minus one in each later iteration until come to zero. After making the definition clear, the steps of TS algorithm are explained in Algorithm 1.

In this paper, to begin with, TS algorithm gets initial SBSs' transmit power vector $\mathbf{p}$, marked as BSF, which means the vector chosen is best so far and will change during the iterations. Set initial algorithm parameters. All entries of the tabu matrix are set to 0, the tabu period is set to P. The neighbor range is set to r, the change of transmit power is 1 dBm per unit, so that the difference between the changed element and the one in the given vector must be no more than rdBm.

Algorithm 1. CCO based on tabu search algorithm.

```
Initialization:
BSF = p
FBest = F(p)
Tmtx = zeros;
for m_iter iterations do
    found = 0
    l = 1
    for lth MBS do
        find neighborhood vectors of BSF, only change elements corresponding to the lth MBS
        calculate F of these neighborhood vectors
        for all F of the neighborhood vectors do
            find the best F of these neighborhood vectors
            if the best F > FBest, or the best F < FBest but "non-tabu" then
                update FBest with the best F
                update BSF with the best neighborhood vector
                mark BSF "tabu" and update corresponding entries in tabu matrix with P
                found = 1
                Break
            end if
            exclude the best vector from the neighborhood vectors
        end for
        if found = 0 then
            update FBest with the oldest best F
            update BSF with the oldest best neighborhood vector
            mark BSF "tabu" and update corresponding entries in tabu matrix with P
        end if
    end for
    update entries of tabu matrix as: Tmtx = max {Tmtx − 1, 0}
end for
return BSF and FBest
```

Set the maximum number of iterations to m_iter. Calculate initial value of the combined function $F(\mathbf{p})$ according to 4, marked as $FBest$ which reveals the best optimization function when iterating. Also, set a bool flag, $found$, which is initialized to be 0 and denotes whether the best vector among neighboring vectors has been found or not.

The search algorithm described above is terminated if the maximum number of iterations m_iter is reached. And our final solution vector BSF has been found before the iteration was stopped. The SBSs transmit power can be updated according to the gotten BSF. Thus, the coverage and capacity optimization has been optimized in the ultra-dense small cell network by using the improved TS algorithm.

4 Simulation Results

In this section, we apply the TS algorithm proposed in system-level simulation and evaluate the combined function to judge the performance, in contrasting with SA approach. In the following, we first introduce our simulation scenario, and then compare the TS and the SA algorithm upon the combined performance, the coverage performance and the capacity performance.

4.1 Scenario

Consider a hot-spot area, for example the area around office building, with MBSs deployed outdoor and SBSs indoor. The indoor clusters are uniformly random within 2 sectors of macro geographical area. And the SBSs are uniformly random

Table 1. Scenario configuration

Parameters	Value
MBS layout	Hexagonal grid/19 sites/3 sectors
SBS layout	Clusters and SBS are indoor
System bandwidth per carrier	10 MHz downlink
MBS carrier frequency	2.0 GHz
SBS carrier frequency	3.5 GHz
MBS maximum transmit power	46 dBm
SBS maximum transmit power	24 dBm
Path loss model	Free space, wall penetration, omnidirectional
MBS penetration loss	20 dB
SBS penetration loss	Outdoor: 23 dB, Indoor: 46 dB
Thermal noise density	−174 dBm/Hz
Number of clusters per macro cell	2
Number of small cell per cluster	4
Active UEs per macro cell	60
Proportion of indoor hot-spot UEs	1/3
Inter-site distance	500 m
Radius of cluster	50 m
Minimum MBS-UE distance	35 m
Minimum SBS-UE distance	5 m
Minimum MBS-center of cluster distance	105 m
Minimum center of cluster-cluster distance	130 m
Minimum SBS-SBS distance	20 m
MBS shadowing standard deviation	4 dB
SBS shadowing standard deviation	3 dB
Shadowing correlation distance	50 m
Traffic model	Full buffer
Scheduling algorithm	Round-robin

dropping within the cluster areas. In our system-level simulation, we build the topology of our ultra-dense network, the channel model, resource allocation and the coverage and capacity self-optimization of the SBSs. The abstract topology of the network and its enlarged display with hot-spot areas and UEs are shown in Fig. 1. In the part of resource allocation, we calculate each UE's (including hot users and others) $SINR$, and assigned to certain BS to access to according to $SINR$. Then we apply our proposed TS algorithm to optimize and evaluate the performance. Some crucial parameters in simulation are presented in Table 1. The channel model is set based on requirements of 3GPP TR36.842 (V12.0.0).

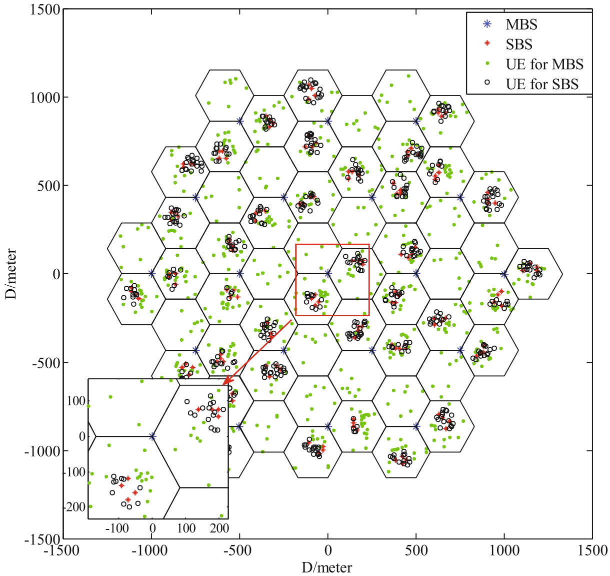

Fig. 1. Scenario of ultra-dense network with densely deployed small cells (Color figure online)

4.2 Analysis

SA is used in simulation in contrast with our proposed TS algorithm. To contrast in the same computational and space complexity, instead of randomly modifying one elements of the last accepted vector, we use a policy similar to TS algorithm for modifying part of vectors in SA. The policy is, finding the best among its neighboring vectors as the modified vector. For fair, the neighbor range comes to be 4, the same as one of neighbor ranges of the TS algorithm simulation.

The parameters concerning the SA are: the initial temperature $T = 3e - 3$, and the parameter T decreases by a scale factor $\eta = 0.998$ over iterations. If the new value of the combined function $F(\mathbf{p})$ is worse than the best so far, calculate the relative difference between the two as the probability pr, and then receive the new vector and the new value with a probability of pr. The parameters concerning the TS are: the initial tabu period $P = 5$, the neighbor range r $\in \{4, 6, 8, 12\}$. Both algorithm begin with the solution vector with all SBSs' power 24 dBm, and the maximum iteration is 30.

As different parameter settings have different influence on the performance of TS algorithm, especially the neighbor range, in addition to contrast with SA, we also compare the performance of different neighbor range. Figure 2 shows that, for the same neighbor range of $r = 4$, our proposed TS algorithm has a significantly faster convergence in iteration than SA, while finally reach almost the same near global optimum as the contrast approach with a gain of about 32%. And the final optima of both algorithms aren't locked into local. On the other hand, we can notice the fact that TS algorithm converges faster under different parameter settings from the perspective of the number of iterations. Nevertheless, higher neighbor range setting means more calculating in each iteration, so the condition of $r = 4$ has the most convergent speed among all the simulation conditions.

Our optimization function is a combined function of CCO. Figure 3 shows the overall throughput of the ultra-dense small cell network. As can be seen from the figure, TS algorithm converges quickly to a constant during the iteration, achieving a gain of 21% capacity improvement. While SA approach only achieves a gain of 15%, lower than the TS algorithm's result. There is an obvious decline in the curve of TS with $r = 12$. That is because that TS can accept a worse solution than the best so far to avoid locking into local optima.

Figure 4 shows the Cumulative Distribution Function (CDF) of the UE throughput in the cells of the final solution. The edge throughput is defined by the one of the 5-tile% UEs' throughput sequence sorting. As can be seen from the figure, the average throughput and edge throughput both improve after the optimization. Besides, on the point of 5-tile%, our proposed TS algorithm also has better performance than the SA.

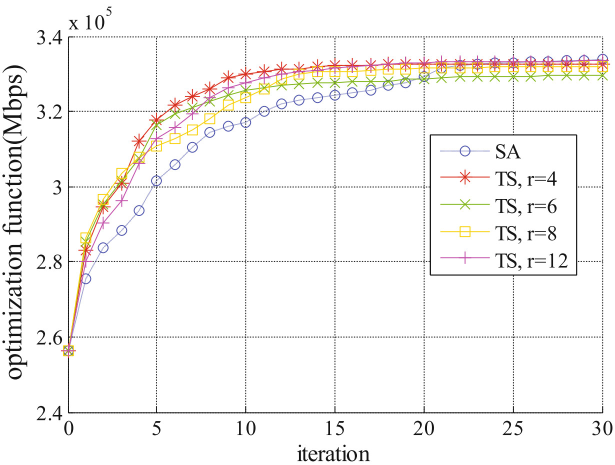

Fig. 2. Combined optimization performance for the TS and SA (Color figure online)

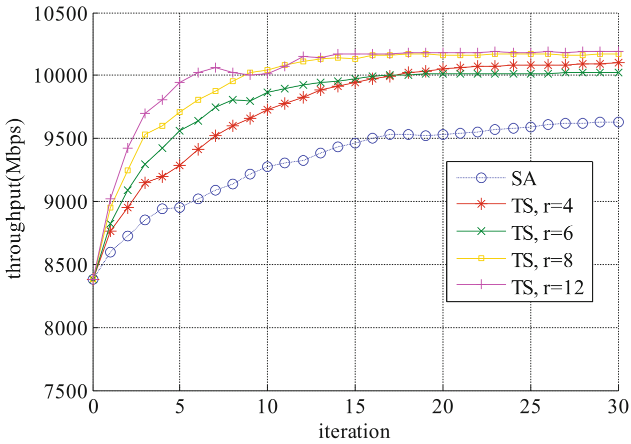

Fig. 3. Overall throughput performance for the TS and SA (Color figure online)

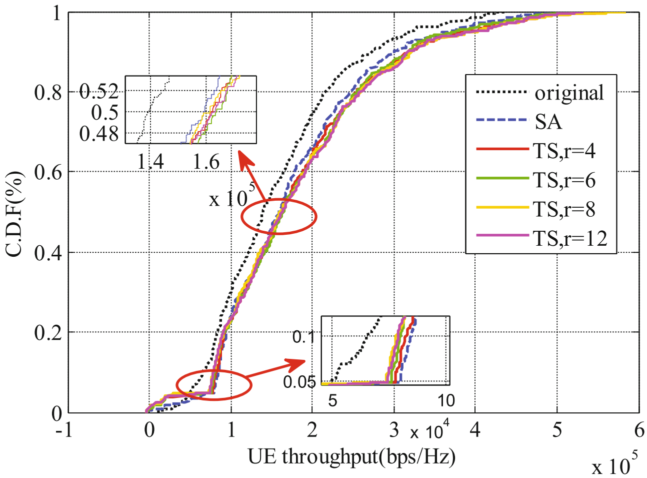

Fig. 4. CDF for UE throughput before and after optimization via the TS and SA (Color figure online)

5 Conclusions

This paper aims to optimize coverage and capacity in ultra-dense network. In order to solve combinational optimization problem, especially when the dimension of the problem is really high and with large amount of data, we introduced the TS algorithm for adjusting parameters under our proposed combined optimization mathematical model. The TS algorithm begins with an initial solution vector and searching for the next solution in its neighborhood, particularly, the algorithm marks some local optima as tabu and try to avoid but not completely prohibit them in later iterative searches. Simulation results show that our proposed optimization model can represent the performance of coverage and capacity well and balance the two conflicting key performance indicators in optimization. More importantly, our proposed TS algorithm improves the coverage and capacity performance significantly with low computational complexity, which means the algorithm can be used for real-time optimization and realize self-optimization for UDN. Besides, from the results obtained in simulation, we can draw the conclusion that the TS algorithm outperforms the adaptive SA approach in terms of convergence speed while achieving near global optimum. Additionally, the TS algorithm proposed in this paper is applied under fixed parameters. Therefore, modifying some parameters adaptive in optimizing process may bring better solution while lowing the computational complexity.

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