Cell PCI Assignment Method Based on Particle Swarm Optimization

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Abstract. In order to streamline PCI allocation within cells for diminished conflicts, interferences, and complexities, an innovative methodology is introduced. A novel approach employing Particle Swarm Optimization (PSO) is employed to gauge and enhance cellular performance in wireless communications. We developed a comprehensive database for 2067 active cells along with their collision, interference, and confusion matrices. Utilizing regression tree models to analyze the influence of PCI configurations on MR values, coupled with PSO's capacity to refine PCI configurations, significantly reduces MR values, consequently boosting network performance. This study exemplifies the effective integration of machine learning and optimization algorithms into enhancing wireless network efficiency, offering network operators a valuable decision-making tool in intricate scenarios.

Keywords: PSO; collision; PCI; network; regression tree; optimization

1. Introduction

In mobile communication networks, the rational planning of physical cell identification code (PCI) is very important, especially in the downlink layer of cell number configuration. Correct PCI planning helps to avoid PCI collision, PCI confusion and PCI Mod 3 interference [1]. If these problems are not properly handled, they will lead to increased inter-cell interference (ICI) and affect the throughput of the physical downlink control channel (PDCCH) [2], especially in the user experience of base station cell coverage edge and signal handover. Considering the limitation of the number of PCI and the large number of cells, PCI must be multiplexed reasonably to optimize resource allocation and reduce downlink ICI, thereby improving network quality. In addition, considering the complexity of the actual network, PCI planning needs to comprehensively consider three main interference scenarios between the neighbors of the same frequency, including PCI collision, confusion, and Mod 3 interference [3], in order to optimize network performance [4]. Using measurement report (MR) data, these data reflect the communication status of the user equipment with the main control cell and neighboring cells through regular reporting, providing a reality-based and accurate evaluation of PCI configuration. For 2067 cells in a region, the goal is to minimize the sum of collision, confusion and Mod 3 interference by redistributing PCI, so as to achieve the purpose of improving network performance [5].

2. Modelling and solving

2.1 Data Preprocessing

In the process of actual network optimization, various data sources can be used to reflect the situations of PCI conflicts, confusion, and Mod 3 interference in the network. Measurement Report (MR) data, periodically reported by user equipment (UE) during communication, include information about the primary cell connected to the UE and the neighboring cells it receives signals from, along with the corresponding signal strength values [6]. Due to their periodic nature, these reports can effectively map the traffic distribution within the network.

The PCI planning problem based on MR data can be summarized as follows: For N cells in the network, collect and process all the MR data for these cells to construct three N×N matrices corresponding to the following [7]:

The collision matrix A = [aij]N×N, where if cell i and j are in the same frequency, then the value of aij is the number of MR in cell i, j is the number of neighboring cells, otherwise the value of aij is 0.

The confusion matrix B = [bij]N×N, where if cells i and j are in the same frequency, the value of bij is the number of MR of neighboring cells in which cells i and j are at the same time of another cell k, otherwise the value of bij is 0.

The interference matrix C = [cij]N×N, where if cell i and j are in the same frequency, the value of cij is the number of MR of the overlapping adjacent cells covered by cell i, j is the number of MR of the overlapping adjacent cells covered by i, otherwise the value of cij is 0 [8].

If cells i and j assign the same PCI value, the number of collisions increases aij + aji, and the number of confusion increases bij + bji. If cells i and j assign the same PCI mod 3 value, the number of mod 3 interference increases cij + cji.

We extracted detailed information for 2067 active cells from the basic network information database, including the identifier, frequency point, and PCI of each cell. Using precise selection methods, we identified these cells for model training and optimization. For these cells, we constructed three matrices representing PCI conflicts, confusion, and interference, providing foundational data for model training.

In our solution, we used regression tree models to study the PCI optimization problem [9]. A regression tree model, a tree-structured machine learning algorithm, is suitable for predicting continuous values. During model training, the PCI values of each cell and its neighboring cells were used as input features, while the values from the conflict, interference, and confusion matrices derived from MR data were used as target variables [10]. Each cell corresponded to three regression tree models to predict the likelihood of conflicts, interference, and confusion. This approach not only enhanced the accuracy of PCI configuration but also supported the long-term stable operation of the network.

2.2 Particle Swarm Optimization

The basic principle of the PSO (Particle Swarm Optimization) algorithm is as follows: a swarm of particles with random states is initialized [11], with each particle representing a feasible solution to the optimization problem. The quality of each particle is determined by a pre-defined fitness function. Each particle can move within the feasible solution space, updating its velocity vector to change direction. Typically, particles move towards the position of the current best particle, iteratively searching for better solutions. In each iteration, particles track both the current best individual (local best) and the best solution found by the entire swarm (global best). The algorithm emulates social behavior, similar to the way a flock of birds transmits information and learns from each other to find the optimal point [12].

The algorithm consists of N particles. During the search process, the position of the i particle in the j-dimensional space is defined as:

$$X_{ij} = \{x_{i1}, x_{i2}, ..., x_{ij}\} \tag{1}$$

The current velocity of each particle is:

$$V = \{v_{i1}, v_{i2}, ..., v_{ij}\} \tag{2}$$

The particle's personal best position is:

$$P_{ij} = \{p_{i1}, p_{i2}, ..., p_{ij}\} \tag{3}$$

The global best position of the entire swarm is:

$$P_{gj} = \{p_{g1}, p_{g2}, ..., p_{gj}\} \tag{4}$$

The velocity update formula for the particles is as follows:

$$V_{ij}^{(t+1)} = V_{ij}^{(t)} + c_1 r_1 (p_{ij}^{(t)} - x_{ij}^{(t)}) + c_2 r_2 (p_{gj}^{(t)} - x_{ij}^{(t)}) \tag{5}$$

where t is the current iteration number, c1 and c2 are learning factors, and r1 and r2 are random numbers between [0, 1]. The formula has three components: the first part is the previous velocity of the particle, the second part is the distance between the current position and the particle's personal best position, and the third part is the distance to the global best position [13].

When particles move without inertia, their next direction is solely determined by their previous velocity. If a particle reaches a local optimum, its velocity decreases, causing other particles to move towards this local optimum, which may reduce the overall solving capability. To enhance the PSO algorithm's performance, inertia is introduced into the velocity update formula [14]. With higher inertia, particles can quickly search the solution space; with lower inertia, they can perform a detailed local search. The velocity update formula with inertia is:

$$\begin{cases} V_{ij}^{(t+1)} = w_i V_{ij}^{(t)} + c_1 r_1 (p_{ij}^{(t)} - x_{ij}^{(t)}) + c_2 r_2 (p_{gj}^{(t)} - x_{ij}^{(t)}) \\ x_{ij}^{(t+1)} = x_{ij}^{(t)} + V_{ij}^{(t+1)} \end{cases} \tag{6}$$

The inertia factor w is updated based on the average fitness level fave and the optimal fitness level fmin, as follows:

$$\begin{cases} w = w_{\min} + \dfrac{(f_i - f_{\min})(w_{\max} - w_{\min})}{f_{ave} - f_{\min}} & f_i \le f_{ave} \\ w = w_{\max} & f_i > f_{ave} \end{cases} \tag{7}$$

The inertia factor w determines the particle's movement range to balance global and local search capabilities, providing better local search ability and faster movement speed.

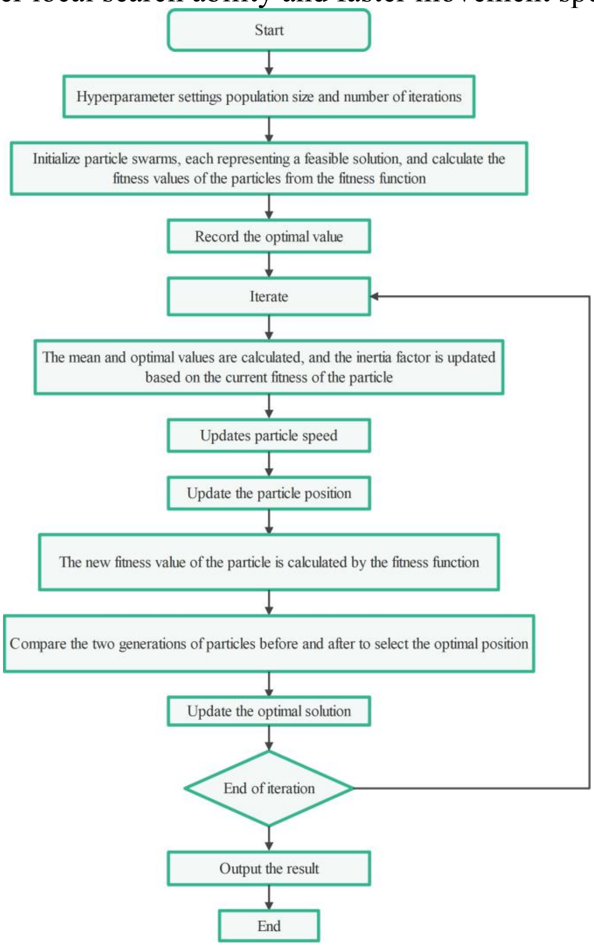

Fig. 1 Flow Chart of Particle Swarm Optimization

2.3 Re-optimization of PCI using particle swarm optimization algorithm

In PSO, each particle represents a potential PCI configuration scheme. Initially, a set of possible PCI configurations is randomly generated, with each configuration represented by its PCI allocation matrix. A fitness function is then defined to evaluate the quality of each particle, that is, the network performance of each PCI configuration. In this study, this is achieved by using the PCI configuration as input to a regression tree model, with the model's output performance metrics serving as the fitness value for that configuration [15].

The specific process is as follows: the performance of each particle in the initial population is evaluated using the regression tree model. Then, according to PSO rules, the particle positions are updated. Each particle adjusts its position based on its historical best position (individual best) and the historical best position of the entire swarm (global best) [16]. The steps of evaluation and update are repeated until the maximum number of iterations is reached.

During the iteration process, the goal is to find a PCI configuration that minimizes the total MR sum by comparing and updating the particle positions. Using the velocity update formula, each particle's position is adjusted by combining individual and global best solutions. The PCI configuration scheme with the highest fitness value is selected from the swarm.

Finally, the optimal PCI configuration is implemented. The optimal PCI configuration found by the PSO algorithm is applied to the actual network, network performance is monitored, and the results are compared with the previous configuration to verify the effectiveness of the optimization.

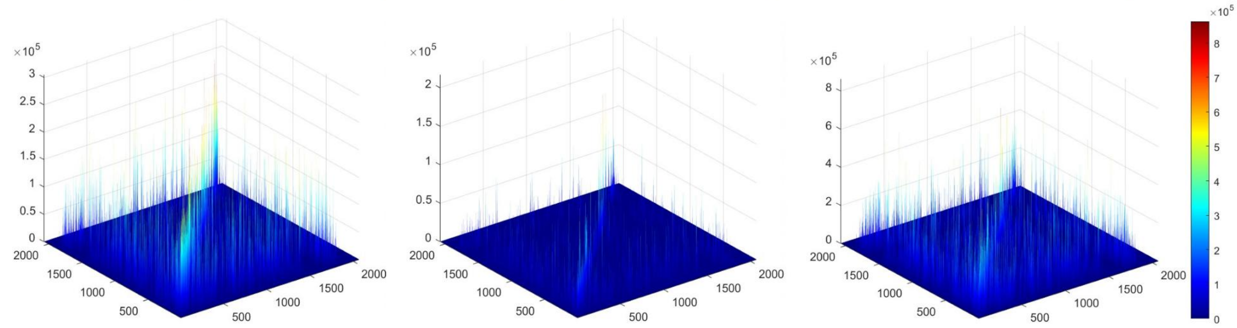

Fig. 2 MR value before optimization(Conflict, Interference, Confuse)

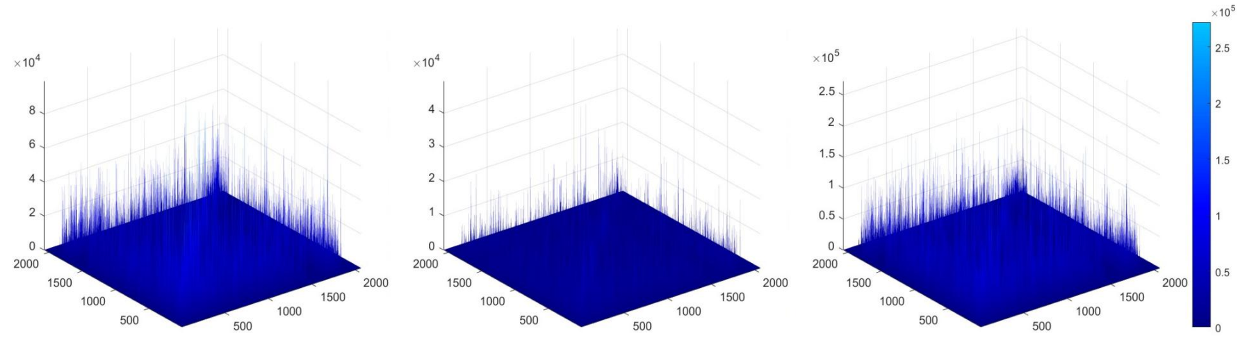

Fig. 3 MR value after optimization(Conflict, Interference, Confuse)

3. Conclusion

This study proposes and validates a PCI optimization method based on regression tree models and the Particle Swarm Optimization (PSO) algorithm. By processing and analyzing a large amount of MR data, PCI conflict, confusion, and interference matrices were constructed to optimize PCI configuration [17]. The results show that this method significantly reduces PCI conflicts and interference, thereby enhancing network performance. Specifically, the total MR value decreased after optimization, with notable reductions in conflict, interference, and confusion MR values.

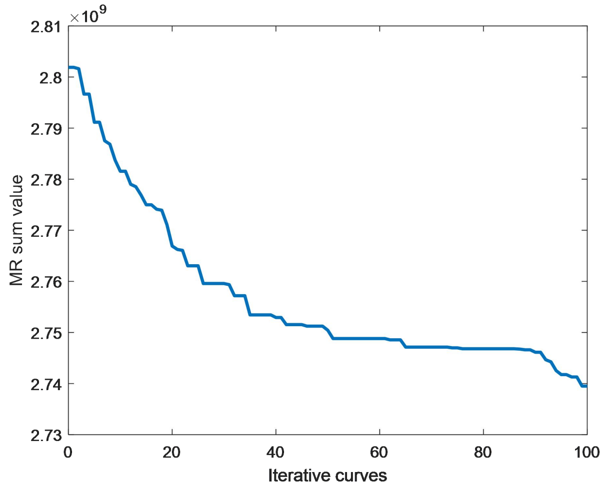

Fig. 4 Iterative plot of MR values

This innovative approach, which combines machine learning and optimization algorithms, offers a new solution for PCI planning in wireless communication networks and has high practical application value. In the future, this method can be further studied and optimized to accommodate larger-scale and more complex network environments, continuously improving network quality and user experience.

4. Discussion

This study presents a novel method for optimizing Physical Cell Identifier (PCI) configuration by combining regression tree models with the Particle Swarm Optimization (PSO) algorithm [18]. This method demonstrates significant advantages in handling complex wireless communication network environments, mainly in the following aspects:

The regression tree model effectively predicts the impact of PCI configurations on Measurement Report (MR) data, while the PSO algorithm continuously iterates to find the optimal solution by simulating the process of information exchange within a swarm. This combination not only enhances prediction accuracy but also significantly improves optimization efficiency, providing a feasible solution for PCI planning in complex environments. By thoroughly analyzing and processing MR data from 2067 active cells, matrices reflecting PCI conflicts, confusion, and interference were constructed. This data-driven optimization approach accurately reflects the actual issues present in the network, allowing for the development of more targeted optimization strategies [19].

Post-optimization, the total MR value of the network significantly decreased from 2,921,598,690 to 2,739,509,468, reducing the number of PCI conflict MRs, interference MRs, and confusion MRs. These results demonstrate the effectiveness of the proposed method in practical applications, capable of significantly reducing PCI conflicts and interference, thereby enhancing network performance. This optimization method not only proves its effectiveness theoretically but also validates its practical implementation in real networks [20]. The optimized PCI configuration performed excellently in field tests, further confirming the feasibility and practicality of combining regression tree models with the PSO algorithm. This provides operators with a practical tool for network optimization.

In summary, this study provides an innovative algorithmic combination to address the PCI planning problem. This method excels in both optimization efficiency and effectiveness, offering valuable insights for future wireless communication network optimization.

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