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5G Network Deployment Scheme and Communication Efficiency Optimization Method for Intelligent Manufacturing

Jun-Xia Zhang[1,2], Meng-Ying Yang[1],
Xin-Hong Hu[1], and Shao-Ting Liu[1*]

[1] Hebei Institute of Mechanical and Electrical Technology,
Xingtai City 054000, Hebei Province, China
{junxia9987, mengying20180107, xinhong5817, shaoting6677}@163.com

[2] Intelligent Sensor Network Application Technology Innovation Center,
Xingtai City 054000, Hebei Province, China

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Abstract. This article addresses the deployment of 5G networks in intelligent manufacturing factories, focusing on issues such as high energy consumption, signal coverage efficiency, and minimizing deployment costs. Initially, models for the workshop, macro base stations, and micro base stations are simplified and quantified. This leads to the construction of models for minimizing base station energy consumption, minimizing base station deployment costs, and optimizing 5G network coverage. Simultaneously, full network coverage in these models serves as the cut-off condition. To find the optimal solution, this article employs an integrated algorithm that combines an improved K-means clustering algorithm with the NSGA-III algorithm. Additionally, the algorithm incorporates the Adam gradient descent method for iteration, enabling the clustering of network nodes from terminal devices in the factory. This approach not only reduces computational complexity but also enhances the algorithm's global search and convergence capabilities. Through simulation experiments, our method effectively identifies the optimal solution for 5G deployment schemes. Furthermore, the improved algorithm demonstrates superior convergence performance compared to its predecessor, thereby validating the feasibility of our approach.

Keywords: 5G, NSGA-III, smart factory, optimal coverage

1 Introduction

Smart factory is a factory that fully utilizes the new generation of information and communication technology to highly interconnect production equipment, processes, personnel, and other aspects, achieving intelligent, flexible, and adaptive production. Smart factories can achieve automation and remote control of production processes through automation and digital technology, reducing reliance on manual labor; Through the Internet and Internet of Things (IoT) technology, the production process can be monitored and managed in real time to reduce the risk of production disruption and supply chain disruption. Therefore, digital transformation and smart factory construction have become inevitable choices for enterprise development [1].

The application of the fifth generation mobile networks (5G), mobile edge computing (MEC), artificial intelligence (AI), industrial Internet and other new generation information communication technologies in intelligent factories can improve the reliability of real-time communication and large-scale data transmission, promote the development of digitalization, informatization and intelligence in the production process, and further promote the digital transformation and intelligent construction of the industry [2].

The application of 5G networks in smart factories has multiple advantages, including high-speed transmission, large connection support, ultra-low latency, and high reliability. These features enable a highly interconnected ecosystem of massive sensors and devices within the factory, enabling real-time monitoring and control of equipment and production processes, as well as meeting performance requirements for time sensitive tasks such

* Corresponding Author

as machine control and equipment collaboration [3]. However, compared to other cellular networks, the high frequency band of 5G networks causes faster signal attenuation and poorer penetration capabilities, leading to issues such as reduced coverage, dense deployment, and increased costs. In addition, interference and noise from metal structures, large equipment, and electromagnetic radiation within smart factories will further weaken the coverage and service quality of 5G signals. Therefore, in order to further improve the performance and service quality of 5G networks in smart factories, this paper studies the key technologies for optimizing the service quality of 5G networks in smart factories, explores the adaptive deployment strategy, high-efficiency communication strategy, and intelligent service quality of 5G networks in smart factories, and thus constructs an efficient and reliable 5G network for smart factories, providing strong support for the digital transformation and intelligent production of factories [4].

5G network is the foundation for large-scale device interconnection in smart factories. Efficient and reasonable deployment of 5G network can effectively improve system capacity and network coverage, and meet the needs of device access and factory applications. However, the optimization and deployment of 5G networks in smart factories presents complexity, requiring not only continuous objective functions such as optimizing device access rates and deployment costs, but also considering discrete variables such as the number and location of base stations. Meanwhile, this problem also involves various constraints such as linear or nonlinear, equality or inequality.

Therefore, this article proposes improvements to the deployment and optimization of 5G networks in intelligent workshops from the following aspects:

1) Based on the heterogeneous network architecture composed of macro base stations and micro base stations, a multi-objective deployment optimization model for intelligent factory 5G network with the highest coverage and lowest deployment cost was established. Then, for the deployment model, the fuzzy analytic hierarchy process was used to analyze and measure the relationship between multiple objectives;

2) Fully utilize the advantages of the improved K-Means algorithm and NSGA-III algorithm, cluster the terminal devices in the factory through the K-Means algorithm, and then effectively explore the search space and find the balance point between network deployment goals by utilizing NSGA-III's strong global search ability and convergence performance.

3) Use MATLAB 2023b simulation software to build a 5G network environment for an intelligent factory, set up the basic production scenario of the factory, and then verify the feasibility of the proposed method through simulation experiments.

2 Related Work

This article summarizes the research results of relevant scholars. There are abundant research achievements on 5G network optimization at home and abroad, but most of these achievements are limited to theoretical improvements and innovations. The research direction of this article is aimed at the application scenarios of smart factories. The relevant research on network base station deployment and network resource optimization is as follows:

Shi Chen, To address the economic optimization scheduling problem of energy storage in base stations with distributed wind power generation active distribution networks, a reliability evaluation model for base stations is established, taking into account two factors: potential power outages and power outage recovery time in the distribution network. The real-time dispatchable capacity of each base station's energy storage is systematically evaluated. Further aiming to minimize system operating costs, an improved twin delayed deep deterministic policy gradient (TD3) algorithm based on the variational auto encoder (VAE) model is adopted to solve the optimal charging and discharging strategy for 5G base station energy storage. Finally, the effectiveness of the proposed method was verified through numerical examples [5].

Li Ma analyzed the propagation attenuation characteristics of 5G signals in rectangular waveguides in coal mine tunnels, and studied the coal mine 5G network from the perspectives of coverage and interference. We selected a ray tracing model suitable for propagation in tunnel environments, analyzed the main factors related to the path loss of coal mine tunnels that affect 5G propagation, such as tunnel cross-sectional size, operating frequency, polarization mode, lobe width, tunnel dielectric constant, tunnel inclination angle, and roughness, and proposed low-frequency networking and narrowband beam solutions. Analyzed the distribution of electromagnetic interference underground, and proposed anti-interference design methods for 5G communication systems in mines from the aspects of electromagnetic radiation generated by loaded coal and rock, mining equipment, frequency converters, and interference sources generated by existing communication network systems underground. A 5G network construction plan for underground coal mines has been proposed, guiding 5G networking and deployment, and proposing upstream and downstream speed indicators to meet the actual production needs of coal mines [6].

Youcheng Shan plans the site selection for the new 5G smart factory base station, taking into account factors such as cost, distance between base stations, and weak coverage point business volume. Through big data visualization analysis, the optimal base station location model is established with the goal of minimizing costs. Secondly, adopting the idea and method of discretization, the focus is on dimensionality reduction and linearization of constraint conditions. In the process of model solving, high-efficiency matrix translation operations are introduced to obtain an optimized mixed 0-1 integer linear programming model. Finally, a targeted site selection scheme was proposed based on the key indicators that the base station can meet 90% of the total business volume of weak coverage points and the distance between the base station and the existing network base station is less than the given threshold value, aiming to provide reliable reference for optimizing the site selection strategy of 5G smart factory base stations [7].

Lu'ao Zhang analyzed the adjustable power consumption characteristics of multiple types of base stations under sleep mechanism and the energy storage regulation capability considering the backup power of the base station, and constructed a flexible spatial quantification model for optical storage 5G base stations. Using Minkowski's method to characterize the spatiotemporal coupling energy trajectory of heterogeneous base station flexible resources, and obtaining the adjustable domain of flexible resource aggregation for massive base station clusters. A collaborative scheduling optimization model for base station cluster aggregation resources to participate in the electricity market and auxiliary service market has been established. A hierarchical distributed base station cluster collaborative optimization scheduling strategy based on the alternating direction method of multipliers (ADMM) has been proposed. The large-scale base station cluster scheduling problem has been reduced and decomposed into three sub problems: unified collaborative peak shaving power response, aggregated power autonomous scheduling, and base station cluster power allocation for solution. Through comparative analysis of numerical examples, it can be concluded that the proposed strategy can reduce the energy consumption cost of communication base stations by 69.86% [8].

Qiqin Yang from Guangzhou summarized that 5G communication networks have the characteristics of high concurrency and low latency. Considering the large number of devices involved in the network, including base stations, antennas, relays, etc., a high-density 5G communication link load balancing testing system based on BP neural network was designed. BP neural network was used to predict the next communication link load value, and the fitness function was combined with the actual load capacity of the link. When the degree of load imbalance reached a minimum, the neural network training was ended to obtain the best solution for communication link load balancing testing [9].

In summary, summarizing the improvement plans of various scholars at the 5G level, this article proposes a 5G network optimization method applied to smart workshops. Chapter 2 mainly introduces the relevant research results and analyzes them to a certain extent. Chapter 3 constructs a model of 5G network base stations, which considers power coverage and usage cost and is used as the optimization target model. Chapter 4 fully utilizes the advantages of the improved K-Means algorithm and NSGA-III algorithm to jointly optimize the multi-objective optimization model of factory 5G network deployment. Chapter 5 is the simulation stage, which constructs a simulation experimental environment for 5G base station deployment. Through optimization and solving, the optimal network coverage is achieved with the minimum number of base stations. The last chapter is the conclusion part, which summarizes the advantages of this article. The research results were analyzed, and the improvement directions in the research aspect of this article were analyzed, Provide direction for further research.

3 Establishment of Network Base Station Deployment Model

At present, the deployment and application of 5G networks in smart factories mainly focus on individual industrial use case scenarios, such as the integration of 5G with AGV, factory critical tasks, remote control, multi robot collaboration, and other application scenarios. There is little research on the global deployment and large-scale coverage of 5G in smart factories. Based on the above application scenarios, issues such as 5G network coverage, power consumption, and signal interference have always existed. Therefore, in order to achieve effective coverage and global deployment of 5G networks in smart factories, this chapter first establishes a multi-objective deployment optimization model for smart factories based on a heterogeneous network architecture composed of macro base stations and micro base stations. Then, for the deployment model, the fuzzy analytic hierarchy process is used to analyze and measure the relationship between multiple objectives, and clustering algorithms and intelligent optimization algorithms are used to solve the model [10].

3.1 Construction of Power Consumption Model

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In smart factories, there are numerous devices with compact layouts. The heterogeneous network composed of macro base stations and micro base stations can significantly improve the coverage and density of the network, supporting the access of more factory equipment and the transmission of massive data. X macro base station providing basic coverage X micro base station deployed under macro base station coverage, and Y Factory Terminal Equipment (FTE) [11], where the set of micro base stations is represented as:

$$C_{mbs} = \{c_{m1}, c_{m2}, \cdots, c_{mx}\} \tag{1}$$

The collection of factory equipment is represented as:

$$C_{pe} = \{c_{e1}, c_{e2}, \cdots, c_{ey}\} \tag{2}$$

The network structure is shown in Fig. 1:

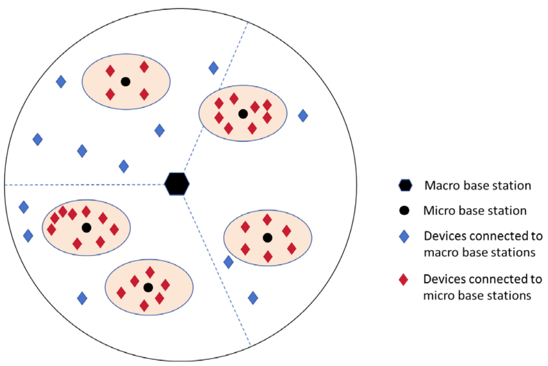

Fig. 1. Schematic diagram of macro base station and micro base station network layout

The purpose of deploying and optimizing the entire 5G network is to provide equipment services throughout the factory. Due to the complex factory environment and high requirements for network coverage, performance, and cost, in order to facilitate the description of 5G network deployment issues in smart factories without loss of generality, this article makes the following simplifications and assumptions:

1) In smart factories, the size, shape, and layout of factory equipment are known, and macro base stations are pre deployed in designated locations. Macro base stations and micro base stations use different operating frequency bands, and interference between them can be ignored.

2) All micro base stations have the same performance and characteristics in terms of hardware and software, and use the same operating parameters for communication, including operating frequency band, antenna height, antenna direction, power control, etc.

3) The interface configuration between all micro base stations and macro base stations is the same, and interface communication is used between micro base stations, ignoring interface noise caused by equipment aging, faults, or incompatibility, and the Channel State Information (CSI) is good.

4) At present, only 5G network deployment is being considered, and signal interference caused by other industrial wireless networks on 5G wireless networks is not currently being considered. 5) In the deployment process of 5G micro base stations, the impact of the motion characteristics and state changes of equipment and machines in smart factories on wireless signals is not currently considered.

6) Assuming that all factory equipment is connected to the 5G network, and each device can only connect to one base station (5G micro base station or 5G macro base station) at a time [12].

3.2 Establishment of Energy Consumption Model for 5G Base Stations

The distribution of production equipment in smart factories varies with location and time, so this section uses non-homogeneous Poisson point [13] processes to model the distribution of equipment. Assuming that the two-dimensional plane area A_p covers the entire factory, $\rho(x, y)$ represents the density function of a certain production equipment appearing at a certain point coordinate in the factory, and $N(Y)$ represents the average number of production equipment in any sub area of the factory area A_p , the expected value is expressed as:

$$E\left[N(Y)\right] = \iint Y\rho(x,y)\,dxdy \tag{3}$$

In the formula, $E[N(Y)]$ represents the expected value, and $dxdy$ is the area element within the factory plane area. Assuming there are $y(i)$ production equipment in a certain area $A_p(i)$, the probability quality function is expressed as follows:

$$\begin{aligned} q\left[y(i)\right] &= e^{-E\left[N(Y)\right]}\frac{\left(E\left[N(Y)\right]\right)^{y(i)}}{y(i)!} \\ &= e^{-\iint Y\rho(x,y)dxdy}\frac{\left(\iint Y\rho(x,y)\,dxdy\right)^{y(i)}}{y(i)!} \end{aligned} \tag{4}$$

By collecting historical or real-time data related to the number or density of devices, including their location, quantity, time, scene, etc; Then select the appropriate model based on the data and determine the parameters of the model. Based on the determined model and parameters, estimate the density function $\rho(x, y)$ by combining historical or on-site data, and describe the distribution of equipment quantity or density [14].

By describing the signal-to-noise ratio, the signal quality received by the device can be described. If the macro base station and micro base station in the factory are always in operation, and in order to improve spectral efficiency, the macro base station and micro base station use the same spectral resources, the device will receive interference from other micro base stations on the same layer and interference from macro base stations across layers [15]. If device $c_{ej,j\in[1,y]}$ is connected to micro base station $c_{mi,i\in[1,x]}$, the signal-to-noise ratio is expressed as:

$$SINR_{ij} = \frac{P_{c_{mi}} \cdot l_{ij}^{\lambda}}{P_{Mbs} \cdot l_{Mi}^{\lambda} + \sum_{i'=1}^{x} P_{c_{mi}} \cdot l_{i'j}^{\lambda} + \sigma^2} \tag{5}$$

In the formula, $P_{c_{mi}}$ represents the transmission power of the micro base station, l_{ij}^{λ} represents the distance between micro base station $c_{mi,i\in[1,x]}$ and device $c_{ej,j\in[1,y]}$, λ represents the path loss factor, P_{Mbs} represents the transmission power of the macro base station, l_{Mi}^{λ} represents the distance between the macro base station and device $c_{ej,j\in[1,y]}$, $l_{i'j}^{\lambda}$ represents the distance between the micro base station $c_{mi',i'\in[1,x]}$ and device $c_{ej,j\in[1,y]}$, and σ^2 represents the noise power. The numerator represents that device $c_{ej,j\in[1,y]}$ receives useful signals from micro base station $c_{mi',i'\in[1,x]}$, the first term of the denominator represents that device $c_{ej,j\in[1,y]}$ receives interference signals from macro base stations, and the second term of the denominator represents that device $c_{ej,j\in[1,y]}$ receives interference signals from other micro base stations.

According to the heterogeneous cellular network system model, it is known that a device can only access one base station at a time. Therefore, A_{ij} is set to indicate whether device $c_{ej,j\in[1,y]}$ is connected to micro base station $c_{mi',i'\in[1,x]}$. The specific meaning is as follows:

$$A_{ij}=\begin{cases}1 & \text{Device } c_{ej,j\in[1,y]} \text{ connects to base station } c_{mi,i\in[1,x]}\\ 0 & \text{Device } c_{ej,j\in[1,y]} \text{ is not connected to base station } c_{mi,i\in[1,x]}\end{cases} \tag{6}$$

A user can only access one base station at a time, so at any time within the cell, A_{ij} meets the following conditions:

$$\sum_{i\in[1,x],j\in[1,y]} A_{ij}=1 \tag{7}$$

Therefore, formula 5 can be expressed as:

$$SINR_{ij}=\frac{P_{c_{mi}}\cdot l_{ij}^{\lambda}\cdot A_{ij}}{P_{Mbs}\cdot l_{Mi}^{\lambda}A_{ij}+\sum_{i'=1}^{x}P_{c_{mi}}\cdot l_{i'j}^{\lambda}\cdot\left(1-A_{ij}\right)+\sigma^{2}} \tag{8}$$

Therefore, it is inferred that the channel capacity obtained by device $c_{ej,j\in[1,y]}$ is represented as:

$$C_{cij}=B_{wij}\cdot\log_2\left(1+SINR_{ij}\right) \tag{9}$$

In the formula, B_{wij} represents the bandwidth occupied by device $c_{ej,j\in[1,y]}$ accessing base station $c_{mi',i'\in[1,x]}$, and the channel capacity of base station $c_{mi',i'\in[1,x]}$ is expressed as:

$$C_{ci}=\sum_{j=1}^{y}A_{ij}\cdot B_{wij}\cdot\log_2\left(1-SINR_{ij}\right) \tag{10}$$

After obtaining the channel capacity expression for a single base station, the total channel capacity within the macro factory can be obtained by summing up the channel capacities of all base stations in the macro factory:

$$C_{c,total}=\sum_{i\in[1,x]}\sum_{j=1}^{y}A_{ij}\cdot B_{wij}\cdot\log_2\left(1-SINR_{ij}\right) \tag{11}$$

The power consumption of base stations is divided into sleep power consumption and working power consumption. In this article, the base station remains in working state, and the power consumption of micro base station $c_{mi,i\in[1,x]}$ is expressed as:

$$Power_{c_{mi,i\in[1,x]}}=P_{const}+\beta\cdot Power_{out} \tag{12}$$

Among them, $Power_{const}$ is the constant power of the micro base station, $Power_{out}$ is the transmission power of the micro base station, and β is the frequency conversion factor of the power amplifier. Setting $Power_{Mconst}$ as the constant power of the macro base station and $Power_{Mout}$ as the transmission power of the macro base station, the total power consumption of the macro factory is the sum of the micro base station power consumption and the macro base station power consumption. Therefore, the power consumption $Power_{total}$ of all base stations can be expressed as:

$$Power_{total} = Power_{Mconst} + \beta \cdot Power_{Mout} + \sum_{i=1}^{x}\left(P_{const} + \beta \cdot Power_{out}\right) \tag{13}$$

The energy efficiency of the entire macro factory is represented as:

$$\begin{aligned} Enery &= \frac{C_{c,total}}{Power_{total}} \\ &= \frac{\sum_{i\in[1,x]}\sum_{j=1}^{y} A_{ij} \cdot B_{wij} \cdot \log_2\left(1 - SINR_{ij}\right)}{Power_{Mconst} + \beta \cdot Power_{Mout} + \sum_{i=1}^{x}\left(P_{const} + \beta \cdot Power_{out}\right)} \end{aligned} \tag{14}$$

3.3 Establishment of Deployment Cost Model

To achieve maximum network coverage, it is often necessary to increase the number and investment of network infrastructure to cover a wider area. However, having too many base stations will increase deployment costs, thereby increasing the overall cost of the network, including infrastructure costs, customized software and system optimization costs, network operation and maintenance costs, network security costs, etc. In order to reduce the deployment cost of 5G networks in smart factories, it is necessary to minimize the number and scale of base stations as much as possible, but too few base stations will also reduce the coverage and quality of the network. Therefore, in the process of network deployment, in addition to ensuring network coverage, deployment costs also need to be considered [16].

To simplify the model, assuming C_M and $C_{c_{mi}}$ represent the deployment costs of a single macro base station and a single micro base station, respectively, and N_M and $N_{c_{mi}}$ represent the deployment quantities of macro base stations and micro base stations, the optimization problem of minimizing the deployment cost of 5G networks in smart factories can be expressed as:

$$\begin{cases} C_{\min} = \min\limits_{N_M, N_{c_{mi}}}\left(C_M \cdot N_M + C_{c_{mi}} \cdot N_{c_{mi}}\right) \\ \left(C_M \cdot N_M + C_{c_{mi}} \cdot N_{c_{mi}}\right) \le C\max \\ \sum_{j=1}^{y} B_{wij} \le B_{\max} \end{cases} \tag{15}$$

In the above formula, Cmax represents the minimum budget cost, and $B_{\max}$ represents that the total bandwidth occupied by the network does not exceed the maximum allowable bandwidth of the base station system.

3.4 Establishment of Network Coverage Model

In real-world scenarios, the coverage pattern of each base station usually follows a circular perception model. As the distance from the center point increases, the coverage capability decreases. Therefore, the deployment plan for base stations involves both the determination of the center coordinates of the base station and the determination of the distance between the base station and the equipment, as well as the determination of the number of base stations. Therefore, the established base station deployment optimization model includes parameters such as location and center distance waiting for solutions [17].

As can be seen from the previous chapters, l_{Mi}^{λ} and $l_{i'j}^{\lambda}$ respectively represent the distance between the device and the macro base station and micro base station. The network transmission signal strength gradually decreases with increasing distance, and the data transmission capacity of the base station also gradually decreases with increasing distance from the target. According to formula 6, when the production equipment point is located within the coverage area of the macro base station or micro base station node, the information collection probability A_{ij} shows a negative exponential decay with the increase of the distance l^{λ} between the location of the equipment and the base station node. When the equipment in the factory is located outside the coverage range of the base station node, the base station node cannot detect any information about the location of the equipment, that is, the collection probability is 0. Considering that device points within the network may be covered by multiple base stations and transmit information, it is assumed that the probability of device coverage can be calculated by multiplying the probabilities collected by each base station. Let P_{cov} represent the probability of information collection points within the sensor network area being covered by the base station node j , and its calculation method is as follows:

$$P_{\text{cov}} = 1 - \prod_{i} \left(1 - A_{ij}\right) \tag{16}$$

When the information transmission probability of the base station exceeds a certain threshold T_{cov} , the base station can be considered to be “effectively covered”. Therefore, the coverage variables of base stations within the network are defined as follows:

$$v_j = \begin{cases} 1 & T_{\text{cov}} \geq P_{\text{cov}} \\ 0 & T_{\text{cov}} \leq P_{\text{cov}} \end{cases} \tag{17}$$

To further measure the deployment performance of base stations, this paper proposes a calculation method for network coverage indicators [18]. Firstly, discretize the continuous 5G base station network to form network grid points, and label all grid points sequentially. Then, this article uses the coverage of grid points as an approximate indicator of the overall coverage of the base station network. Therefore, the calculation method for the network coverage index can be obtained as follows:

$$C = \frac{\sum v_j}{W} \tag{18}$$

In the formula, W represents the number of grid points obtained after discretization and segmentation. On the basis of introducing the node perception model and coverage model, it is necessary to establish a mathematical model to describe how to optimize the deployment of macro and micro base stations. Firstly, divide the 5G network into grids and label the discretized grid points in order as 1, 2, 3, ..., W, Use (D_{xi}, D_{yi}) to represent the coordinates of the discretized grid points labeled i . Then, the variable β_i is introduced to indicate whether the base station is deployed at the discretized grid point labeled i, as follows:

$$\beta_i = \begin{cases} 1 & Y \\ 0 & N \end{cases} \tag{19}$$

When the value of β_i is 1, it indicates that base stations are deployed within the grid. When the value of β_i is 0, base stations are not deployed within the grid. Network coverage is an important indicator for measuring the deployment performance of network nodes. The general deployment principle is to deploy as few base stations as possible to reduce cost while meeting coverage requirements. Therefore, the objective function of the optimization model for base station deployment can be expressed as follows:

$$\min \sum_{i=1}^{W} \beta_i \tag{20}$$

Therefore, after the above modeling process, the overall optimization objective of this article is to achieve the lowest total energy efficiency, deployment cost, and optimal network coverage. Therefore, the formula for the overall optimization objective is:

$$F(x) = C_{\min} + Enery_{\min} + \min \sum_{i=1}^{W} \beta_i \quad \textbf{(21)}$$

After the above process, the establishment of a model for effective coverage and global deployment of 5G networks in smart factories has been completed. Based on the heterogeneous network architecture composed of macro base stations and micro base stations, the model considers the multi-objective deployment optimization model that maximizes the coverage of 5G networks in smart factories, minimizes network deployment costs, and maximizes the coverage range after network deployment. Then, for multi-objective and nonlinear integer programming models, fuzzy analytic hierarchy process [19] and gradient solving method [20] are used to analyze and measure the relationships between multiple objectives, and clustering algorithm and intelligent optimization algorithm are used to solve the model.

4 Dual Objective Optimization Method Based on NSGA-III

In the deployment of 5G networks in smart factories, the data scale involved is usually large. Clustering the terminal devices in the factory through the K-Means algorithm [21] can help reduce computational complexity. NSGA-III [22] has strong global search ability and convergence, which can effectively explore the search space and find the balance point between multiple optimization objectives. Therefore, this section fully utilizes the advantages of the improved K-Means algorithm and NSGA-III algorithm to jointly optimize the multi-objective optimization model for factory 5G network deployment. At the same time, in the process of solving the optimal coverage of the deployment model, an iterative algorithm needs to be added to solve the model. When the total number of base stations is fixed, the optimal base station network deployment can be obtained by solving the nonlinear programming model of the base station network deployment. Deployment plan and corresponding regional information coverage. Then, gradually increase the number of base stations and repeat the calculation to find the best solution until comprehensive coverage of the network area is achieved. When solving for base station coverage, gradient descent is integrated into the algorithm. Gradient descent is a common parameter optimization method in numerical calculations, which iteratively optimizes parameters along the negative gradient direction of the loss function until the loss function converges to or near the minimum value. The specific process is shown in Fig. 2.

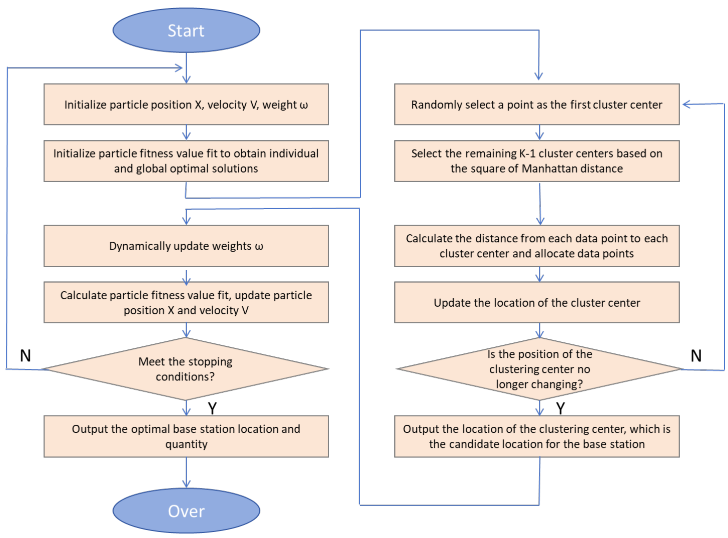

Fig. 2. Schematic diagram of algorithm flow structure

Integrate the improved differential evolution algorithm with the K-Means clustering algorithm, calculate the fitness function value of each individual, use the improved differential evolution algorithm for iterative optimization, and replace the initial cluster center randomly selected by the traditional K-Means clustering algorithm with the optimal individual output at the end of the algorithm. The calculation formula is as follows:

$$fitness = \sum_{i,k}\left(s_{i,k} - c_k\right)^2 \quad \textbf{(22)}$$

In the formula, $x_{i,k}$ represents a data point, and c_k represents the center of the cluster to which the data point belongs. The smaller the calculated value, the better the clustering effect, and vice versa, the worse the clustering effect. In clustering algorithms, the ultimate goal is to minimize the density of data points within a class and maximize the density between classes. Therefore, the sum of squared errors is used as the fitness function for improving the differential evolution algorithm.

1) Set the population size to 10 times the solution dimension, adaptively adjust the mutation factor and crossover factor, set the current number of evolutions to G, the maximum number of algorithm evolutions to $G_{\max}$ = 1000, and the Gaussian perturbation coefficient to $C = 0.1$.

2) Initialize the population size.

3) Perform improved mutation operations on individuals in the population to obtain mutated individuals

4) Perform improved crossover operations on parent individuals and mutant individuals to obtain intermediate experimental individuals.

5) Calculate the fitness values of the parent individual and the intermediate experimental individual separately, and compare the fitness values. Individuals with better fitness will enter the next generation population and continue to participate in evolution. Repeat steps 3) to 5) until the maximum number of iterations of the algorithm is reached.

6) Cluster the optimal individual output by the algorithm as the initial cluster center of K-Means, iterate iteratively until the stopping requirement or maximum iteration times are met, and the algorithm ends, outputting the clustering results.

7) When the total number of sensor nodes is fixed, randomly set the values of optimization model decision variables within the allowable range to complete the preset deployment of base stations.

8) To alleviate the problems of memory overhead and slow update speed, randomly select some base station samples and calculate the average gradient value. The calculation formula is as follows:

$$G = \frac{\nabla_{\phi}\sum_{i=1}^{W} L\left(\beta_i, R_i\right)}{W} \quad \textbf{(23)}$$

In the formula, R_i represents the network coverage radius. Then use the Adam gradient descent method for iteration. When the loss function satisfies the following conditions, the iteration stops and the result is output.

This article uses the best point set strategy to improve the population initialization method, and names the improved algorithm i-NSGA-III algorithm. The integer decision variables in this article are encoded in binary, while the real number decision variables are encoded in real value. The spatial randomness of real valued variables is relatively high, so the optimal point set initialization method is adopted for the solution space composed of real valued decision variables, where the real valued decision variables are the proportion of participants δ and the learning rate η , and the spatial dimension is, assuming a population size of 2. The specific steps are as follows:

1) Calculate the value of r :

$$r = \left(r_1, r_2, \cdots, r_n\right) \quad \textbf{(24)}$$

$$r_i^k = \mathrm{mod}\left\{2i\cos\left(\frac{2\pi k}{p}\right)\right\} \quad \textbf{(25)}$$

2) Construct a set of optimal points based on the population size n;

3) Map the set of good points to the domain;

The first generation of parental population generates offspring individuals through selective crossover mutation. Then calculate the four target values for the offspring, mix the parent and offspring populations, perform non dominated sorting, select a new parent population, and repeat until the iteration stop condition is met. The pseudocode evaluated for each population in the improved algorithm is shown below:

```
Input:
    PopulationSize: Number of solutions in the population
    Generations: Number of generations to evolve
    K: Number of clusters for K-means
    ObjectiveFunctions: Functions to evaluate objectives of solutions
    ProblemConstraints: Constraints defining the feasible solution space
 Initialize:
    Population <- GenerateInitialPopulation(PopulationSize, ProblemConstraints)
    EvaluatePopulation(Population, ObjectiveFunctions)
    Fronts <- NonDominatedSorting(Population)
    ReferencePoints <- GenerateReferencePoints()
    Association <- InitializeAssociation(Fronts, ReferencePoints)
 for generation = 1 to Generations do
    # Selection
    MatingPool <- SelectMatingPool(Population, Fronts, Association)
     # Crossover and Mutation
    Offspring <- ApplyCrossoverAndMutation(MatingPool)
    EvaluatePopulation(Offspring, ObjectiveFunctions)
     # Combine Parent and Offspring Populations
    CombinedPopulation <- CombinePopulations(Population, Offspring)
     # Non-dominated Sorting and Crowding Distance Assignment
    NewFronts <- NonDominatedSorting(CombinedPopulation)
    for each front in NewFronts do
        AssignCrowdingDistance(front)
     # Apply K-means Clustering to Enhance Diversity
    ClusteredSolutions <- KMeansClustering(CombinedPopulation, K)
     # Environmental Selection
      SelectedSolutions <- EnvironmentalSelection(NewFronts, Association,
ReferencePoints, ClusteredSolutions)
     # Update Population
    Population <- SelectedSolutions
     # Update Association and Reference Points if necessary
    UpdateAssociation(Association, SelectedSolutions, ReferencePoints)
 end for;
```

By using the K-Means algorithm to cluster the network nodes of terminal devices in the factory, the computational complexity is reduced. NSGA-III has strong global search ability and convergence, which can effectively explore the search space and find the balance point between multiple optimization objectives. At the same time, the addition of iterative algorithm solving algorithm can help solve the network coverage model constructed in this paper. This section provides a complete network model structure and the improvement process of the algorithm, and completes the detailed description of the algorithm solving steps. Finally, a typical pseudo code structure is given. Further simulation experiments are needed to verify the accuracy of the optimization mathematical model and algorithm solution constructed in this paper.

5 Simulation Experiment and Result Analysis

This section optimizes the deployment of 5G base stations based on the distribution of networked devices required for actual smart factory production sites. Through the optimized deployment plan, the optimal number of devices and the most reasonable network coverage capability are obtained.

5.1 Simulation Environment Settings

The distribution of equipment in a factory is closely related to equipment functions, production processes, job requirements, space utilization, and other factors. In some areas, there are a large number of sensors or small devices, resulting in a high density of devices in the area, while in some areas, the concentration of large devices leads to a relatively low density of devices in the area. In order to simulate smart factories with different device densities, this section uses MATLAB 2023b simulation software to construct a 5G network environment for smart factories [23]. The factory's footprint is set to $1500 \times 1500 m^2$, and the spatial distribution of factory terminal devices follows the density function $\rho(x, y)$. The device distribution diagram in the simulation scenario is shown in Fig. 3.

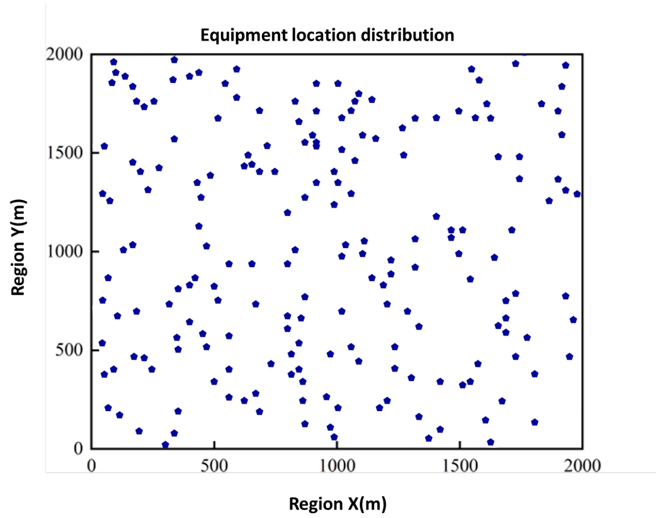

Fig. 3. Intelligent factory 5G network simulation scenario

5.2 Comparison of Optimization Results

Use improved K-Means for local search and improved NSGA-III algorithm for global search. By locally searching each cluster, network coverage can be improved and deployment costs can be reduced. By globally searching the entire population, the dual optimization goals of network energy efficiency and deployment costs can be further optimized. The optimization results are shown in Fig. 4.

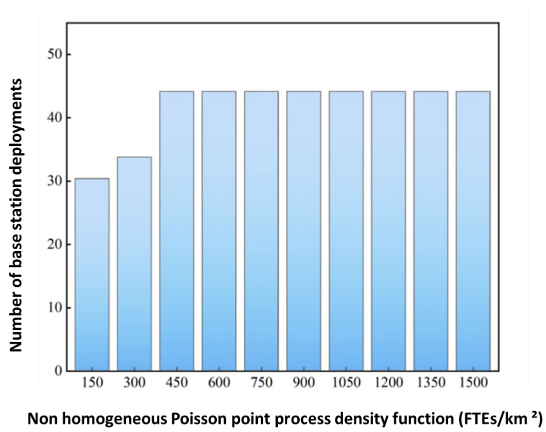

Fig. 4. Schematic diagram of deployment quantity of base stations with different density functions

From the graph, it can be seen that as the number and density of terminal devices in the factory increase, the number of base stations deployed within the area also gradually increases, and when the non-homogeneous Poisson point process density function is constant, the deployment number of base stations is 50. Due to the limitations of factory space size and base station deployment costs during the experiment, the maximum allowed number of base stations to be deployed in the area was set at 50.

As shown in Fig. 5, it is the obtained base station deployment distribution map.

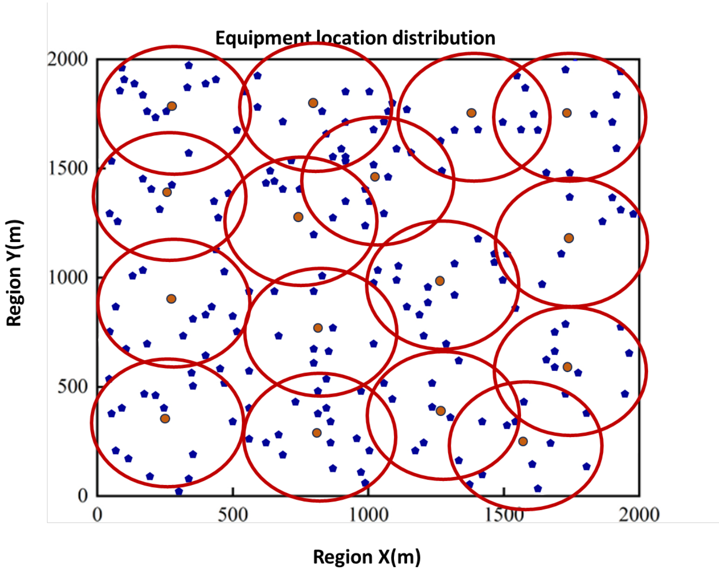

Fig. 5. Distribution diagram of base station deployment

From the results, it can be seen that the coverage of relative intersections is relatively low, and the minimum base station achieves optimal coverage. As shown in Fig. 6, it is the variation curve of network energy efficiency with the number of micro base stations. As the number of micro base stations in the region increases, the network energy efficiency of all algorithms shows an increasing trend. When a certain value is reached, the network energy efficiency does not continue to increase with the increase of micro base stations. On the contrary, as the number of micro base stations increases, the network energy efficiency shows a decreasing trend. As the number of micro base stations increases, it will inevitably cause an increase in network energy consumption, and the interference between base stations in the region will also increase, leading to a decrease in network energy efficiency.

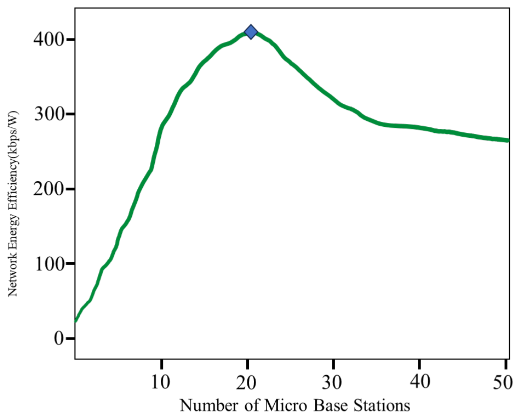

Fig. 6. Network energy efficiency changes with the number of base stations

6 Conclusion

The high operating frequency band and complex factory environment pose challenges to the deployment and application of 5G networks in smart factories. A large number of metal structures, concrete walls, and equipment can interfere with and weaken the transmission of high-frequency 5G signals, affecting the coverage and signal quality of the network. Interference sources such as high-intensity electromagnetic radiation can interfere with the transmission and reception of 5G signals, leading to unstable signals and reduced network performance. Although intensive deployment meets the network connectivity requirements of large-scale and high-density equipment in factories, it also leads to problems such as network interference, deployment costs, network energy consumption, and increased difficulty in network resource management. In order to address these issues, this article mainly focuses on the adaptive deployment strategy and high-efficiency communication strategy of smart factory 5G network, aiming to form a method and technical system for optimizing the service quality of smart factory 5G network, and provide key support for enterprise digital transformation. The main research contents are as follows: A deployment strategy for smart factory 5G network based on improved K-Means and NSGA-III is proposed. Firstly, considering the complexity of the factory environment, a digital description and modeling of the distribution of equipment in the factory were conducted to accurately describe the transmission of 5G signals in the factory; Secondly, to ensure the network coverage and quality requirements of the smart factory, a multi-objective deployment optimization model for the 5G network of the smart factory was constructed, which comprehensively considers network coverage, network deployment costs, and base station energy efficiency. Finally, a two-stage iterative optimization algorithm based on improved K-Means and NSGA-III was designed to effectively solve the multi-objective deployment optimization model and obtain the optimal deployment location and number of base stations.

This article focuses on the key technologies for optimizing the service quality of 5G networks in smart factories, including optimization deployment, high-efficiency communication, etc., and has made significant progress in basic research. These efforts can to some extent accelerate the deployment and application of 5G networks in vertical fields such as smart factories, promoting the development of industrial automation and digital transformation. However, with the continuous in-depth research on the problems and the investigation of the current situation and needs of enterprises, there are still certain limitations in existing research, and there are still many issues that need to be further studied:

1) In addition to considering the impact of device distribution and factory environment on network deployment, there are also specific business requirements, security requirements, and other factors in smart factories. Integrating more factors into deployment optimization models to achieve more comprehensive network deployment and optimization is a content that needs further research in the future. In addition, although the proposed adaptive deployment method has been validated on the personalized customized intelligent manufacturing factory platform, there may be differences in equipment distribution, process flow, communication requirements, and other aspects among factories in different industries. In the future, further exploration is needed to optimize the service quality of 5G networks in intelligent factories in different industries.

2) Compared with the traditional approach of relying solely on macro base stations for network coverage, the heterogeneous 5G network architecture that combines macro base stations and micro base stations can significantly improve network coverage and capacity, providing higher quality network performance and service quality. This article is based on a two-layer heterogeneous 5G network architecture where a single macro base station and multiple micro base stations coexist. However, in addition to macro base stations and micro base stations, there are other types of base stations that can be deployed in factories, such as mobile base stations composed of drones or other aircraft, and vehicle mounted base stations composed of mobile devices or vehicles. Therefore, future research can further explore the deployment and application of different types of base stations and network architectures in smart factories, and improve related technical solutions.

3) Regarding the various optimization algorithms currently in use, on the one hand, the selection of hyperparameters such as iteration times, learning rates, and number of neurons directly affects the convergence and accuracy of the model. In the future, improvements can be made in automatic parameter tuning, network structure optimization, and learning rate adaptation to achieve efficient setting of hyperparameters. On the other hand, based on various optimization models currently being constructed, model lightweighting methods such as network pruning, weight quantization, and low rank decomposition can be considered to reduce model parameters and computational complexity, achieve model size reduction and improve usability without reducing model accuracy, and promote the popularization and application of 5G network service quality optimization technology for smart factories in different industries.

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