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SPACE LAYOUT SIMULATION OF ASSEMBLED NANOARCHITECTURE BASED ON IMPROVED PARTICLE SWARM OPTIMIZATION

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Abstract. In order to solve the problem that the traditional building space configuration model cannot meet the optimization of building space characteristics, the author proposes the optimization of building space utilization based on spatialized particle swarm optimization. First, to solve the problem of optimal allocation of space units, the PSO algorithm is modified to encode the space units by means of character coding.Secondly, the maximum standardization method is used for data processing, and the factors affecting space utilization are summarized, the objective function of optimal allocation of architectural space is given from three aspects: economic benefits, social benefits and ecological benefits; Finally, by analyzing the advantages and disadvantages of master-slave parallel model and point-to-point parallel model, a chained parallel structure is proposed. The experimental results show that: The experimental data is based on the utilization of building space in these three regions in 2015, and the vector map is divided into 30 m × A grid of 30 m in size, and all statistical data and spatial data are projected on each grid cell. The difference between the fitness values of the final convergence of the three parallel models is small, and the main difference is the convergence speed. During the run time test, set the three parallel models to run under the conditions of 8, 16, 32 and 64 nodes respectively. Because of the combination of the advantages of master-slave model and point-to-point model, the running time of chained parallel model is significantly lower than that of the other two parallel models. Conclusion: Through data simulation test, it is verified that the chained parallel model has higher fitness, convergence speed and shorter running time, and its performance is better than the other two, indicating that the optimization algorithm proposed by the author has good performance.

Key words: Spatialized particle swarm, Building space utilization rate, Symbol coding, Maximum standardization method, Chain parallel model, Master-slave parallel model, Point to point parallel model

1. Introduction. Land use planning is based on the natural and historical characteristics of regional land and social and economic development, comprehensive technical and economic measures to plan and arrange the future land use of the region in advance, reasonably allocate land resources in time and space, and reasonably organize land use. In order to promote sustainable land use, the state has established a national, provincial, municipal, county and township land use planning system. The five level planning model gradually controls the land use structure from top to bottom, and organizes from macro to micro, promotes land use. The main and difficult problem in land use planning is the optimal utilization of land, including the optimization of land use and structure, as well as the optimization of land use,it is not only necessary to determine the proportion of land used by various departments, but also to implement the specific spatial location. Through the optimization of land allocation, determine the best land use ratio, quantity and location of land, that is, solve the problems of “what”, “how much”, “where” in land use planning. The optimal allocation of land use is also a multiple optimization problem. According to the difference of region, the optimization goals are win-win and conflict. In the process of optimization, it is necessary to maintain the interests of all parties, balance the land resources and needs, and maximize the social, economic, and ecological benefits of the regional land use.

The optimal allocation of land use is a hot issue in land use planning. Optimization of the multi-scale structure of land use has achieved the selection of optimization goals and the application of optimization methods, but the research on the theory and methods of optimization of land use in general is a little weak.Based on intelligent optimization algorithms, many scholars have proposed various land use optimization allocation models. However, these models have various problems, which make them stay in the stage of scientific research and fail to be applied to the practice of land use planning. These problems include: The degree of spatialization of the model is not enough, and the spatialization operation is inconvenient; The integrated domain knowledge is weak, which affects the optimization effect of the model; The operation efficiency is low, and it is difficult to apply to high-precision land use optimal allocation in large areas. Study how to make intelligent optimization

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algorithm spatialized, knowledge-based and parallelized, it will greatly improve the optimization effect and efficiency of the land use optimization model, and improve the practicality of the intelligent optimization model.

2. Literature Review. Housing is the basic demand of people all over the world, with the progress of science and technology and social development, the housing construction mode is also improving in exploration, inspired by the booming development of manufacturing industry, people begin to think about whether the construction mode can also take the road of industrialization. The construction industry has always been dominated by cast-in-situ construction [11]. In recent years, Beijing, Shenyang, Shenzhen, Shanghai, Guangzhou, Hong Kong and Taiwan have responded to the requirements of the modernization of the national construction industry, take the lead in promoting the development of prefabricated buildings. Ghahramani, M. believes that off-site manufacturing and standardized production can effectively promote the development of the construction industry in terms of quality, cost, progress, safety and energy efficiency, and has designed and described this to guide the prefabrication and assembly technology [4]. After analyzing the current situation of low efficiency in the construction industry, de Oliveira proposed that prefabrication can be adopted in the construction, based on this, he analyzed different construction projects after adopting the assembly method, and the data obtained proved that the assembly method can indeed reduce a lot of waste [3]. Song, M. pointed out that building prefabrication is the future trend of the industry, and concluded that prefabricated buildings can indeed bring more obvious economic and social benefits through economic, environmental, social and other assessments of prefabricated building projects [13]. Carri ó n, D. pointed out the importance of the layout of temporary materials for the layout management of the construction site, and proposed to quantify the use frequency of a material in the whole project period by the material accessibility level, that is, the daily use of a material, the three key factors affecting the use frequency are: Material handling, transportation route and transportation distance.

Through the data simulation test, the author has verified that the chained parallel model has higher fitness, convergence speed and shorter running time, and its performance is better than the other two, indicating that the optimization algorithm proposed by the author has good performance.

3. Research Methods.

3.1. Spatialization of particle swarm optimization algorithm. In view of the shortcomings of the existing building utilization configuration model in the degree of spatialization, the author adopts the spatialized coding method, operation unit and operation operator. The mapping from numerical space to geographical space is realized based on particle swarm optimization algorithm, and the optimal configuration model of building space utilization is constructed according to rules and multi-agent principle. Finally, the parallel improvement of the particle swarm optimization model is realized by the method of sub cluster division. Its structural framework is shown in Figure 3.1.

For the application of PSO to the optimal layout model of domestic space applications, it is necessary to verify the relation between the parameters of PSO and the parameters of the optimum layout model for the domestic space applications,furthermore, it is necessary to study the application of the PSO to the optimal configuration problem.In order to separate the responsibilities of algorithm engineers and building space planners, the corresponding relationship between the optimal configuration parameters of building space utilization and the parameters in particle swarm optimization should be as comprehensive and accurate as possible. Particle swarm optimization has four parameters: Particle, particle position, particle speed and particle fitness.

In particle swarm optimization, particles are used to represent candidate solutions of the problem to be solved. For the problem of optimal configuration of building space utilization, particles can be defined as the configuration scheme of building space utilization. The particle swarm consisting of all particles represents a collection of multiple configuration schemes, and the particle position is used to represent the value of the building space allocation unit and the use type of the building, generally, the array $(x_1, x_2, \cdots, x_n)$ is used to represent the position of particles, each element in the array represents a dimension, the variable x in the dimension corresponds to the numerical value of the building space allocation unit. Because of the specific definition of particles, their speed in each dimension is defined as the direction of building unit usage conversion corresponding to that dimension. In general, the transformation probability is used to describe the velocity

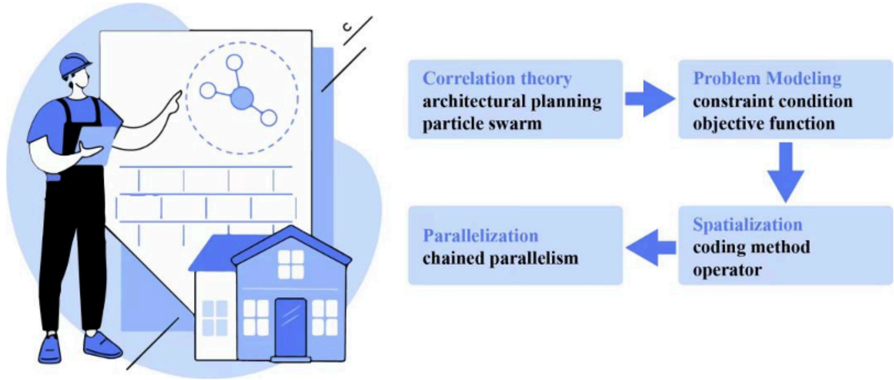

Fig. 3.1: Structure framework of spatialized particle swarm optimization algorithm

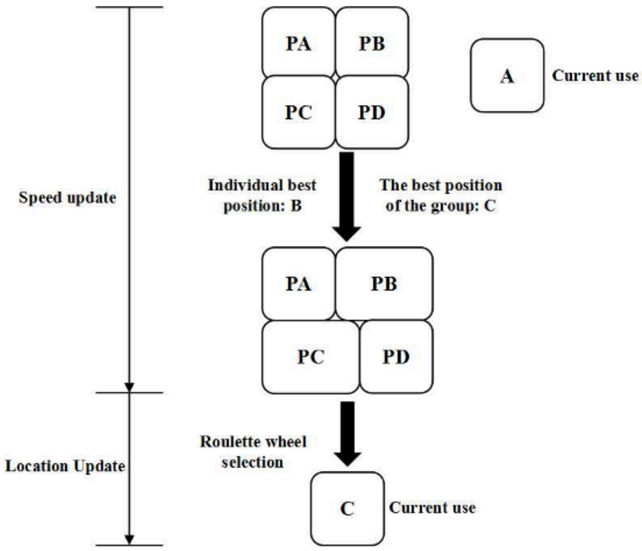

Fig. 3.2: Schematic diagram of particle velocity and position update based on symbol encoding

of particles. The fitness indicates the advantages and disadvantages of the optimized configuration scheme for the utilization of the building cluster, under the limited land and use space, the objective function should be constructed from multiple perspectives, then the fitness function is determined.

For the problem of building space configuration, it is necessary to integrate the characteristics of three-dimensional space for particle swarm optimization, mainly including the spatialization of coding methods, operation units and operators. The author uses symbol - based coding method to encode PSO spatially. Residential buildings are classified into three categories: residential, commercial, industrial, and public, and the values A, B, C, and D, respectively. In PSO, the location of the particle in length is A.The particle velocity is represented by the probability vector $[PA, PB, PC, PD]$, generally, the initial probability vector elements of each particle have the same value. The value change of the particle will be affected by the best historical position of the individual and the best historical position of the population, so the probability of each dimension will change. Finally, the purpose of the building space is finally determined through roulette selection, as shown in Figure 3.2.

3.2. Spatial particle swarm optimization model for optimal allocation of space utilization.

3.2.1. Factors affecting the use of building space. The distribution of architectural space is affected by various factors, and the degree of interaction varies between different regions and varieties.By sorting out the data related to land and buildings in various regions, the weight coefficients of various indicators affecting the use of building space are summarized, and the main impact indicators are selected according to the size of the values. As each indicator has different quantity units and magnitudes, it needs to be standardized. The author adopts the maximum standardization method to normalize the data, as shown in Formula (3.1).

$$D_{ij} = 100 \times d_{ij}/\max(d_i) \tag{3.1}$$

In the formula, D_{ij} represents the normalized value of the jth data of the ith index affecting the utilization and allocation of building space; f_{ij} represents the true value of the jth data of the ith index affecting the utilization and allocation of building space; $\max(d_i)$ represents the maximum value in the ith index [2, 16].

The following main indicators can be obtained after data normalization by formula (3.1): Total amount of land development, urban construction, rural land, industrial and mining land, commercial land, and green land.The above indicators will affect the utilization and configuration of building space to varying degrees, and also affect each other, the specific expression is Formula (3.2).

$$Q_i = af(x_i) + b \tag{3.2}$$

In formula (3.2), Q_i represents the land use index mentioned above; x_i refers to the factors that affect the utilization and allocation of building space, and a and b are weight coefficients and adjustment factors [5].

3.2.2. Objective function of space optimal configuration. In order to improve the utilization rate of building space, it is necessary to optimize the configuration of building space. The objective function is used to evaluate the benefits of the building space configuration scheme, and the accuracy of its expression directly affects the effectiveness of the optimized structure. The author constructs the objective function of optimal allocation of architectural space from economic, social and ecological benefits. The economic benefits are used to evaluate the economic benefits generated by the configuration scheme of the building cluster, which can be quantitatively described by monetized indicators. The author uses the ratio of GDP and building area produced by each building area to characterize the economic benefits of the buildings in this area. However, the total GDP is also related to the degree of economic investment in the region. Therefore, it is necessary to comprehensively consider economic benefits from multiple factors such as land use area, total investment and GDP. Social benefits are used to characterize the ability of buildings in this area to meet people's daily life and work needs, and pay more attention to whether the configuration of building clusters is conducive to social equity and the improvement of people's quality of life. The indicators involved mainly include: Land utilization rate, urbanization rate, traffic network structure index, coverage rate of social service facilities, etc. Compared with economic and social benefits, ecological efficiency pays more attention to the impact of the configuration of building clusters on the ecological environment. In order to meet the economic development mode of "resource saving and environment-friendly", the impact of land use and building configuration on land degradation and soil pollution should be minimized. The author uses forest land coverage, wetland coverage and per capita green land coverage to evaluate the ecological benefits [6, 9].

Assume that the building space utilization rate of each area in a city is represented by $E_1, E_2, E_3, \cdots, E_n$ according to its value. The total building space is expressed in L, and the total building space allocated to each area is $L_1, L_2, L_3, \cdots, L_n$. Therefore, the linear programming model used to plan the optimal allocation of building space utilization in the city can be expressed by equations (3.3) and (3.4).

$$E_i = E(x_i, L_i) \tag{3.3}$$

$$L = L_1, L_2, \cdots, L_n \tag{3.4}$$

In the formula, x_i represents the exogenous element of non construction land. Through the analysis of the author, it can be seen that the realization of the optimal allocation of the utilization of building space is achieved by the cooperation of multiple objectives [12, 14].

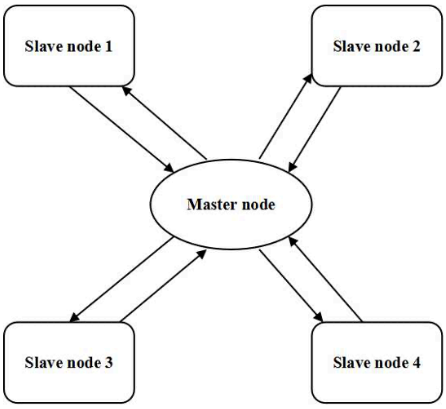

Fig. 3.3: Schematic diagram of master-slave parallel algorithm structure

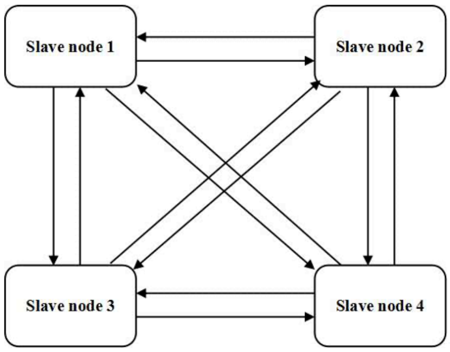

Fig. 3.4: Structure of point-to-point parallel algorithm

3.2.3. Parallel space utilization optimization configuration model. Most of the building space utilization and configuration algorithms are based on serial algorithms, which can not satisfy the needs of large area and high precision. Meanwhile, the serial data transfer takes a long time, which makes it hard to guarantee the timeliness.A parallel algorithm is used to improve the performance of PSO. Parallel algorithms are usually divided into master-slave and point-to-point. The author analyses their merits and demerits and makes improvements on them [20, 10]. In order to meet the requirements of large area, high precision and low time consumption, the author studied the parallelization algorithm of optimal allocation of building space utilization. All the particles are divided into different subsets by sub - clustering, and a parallel particle swarm optimization model is developed according to the corresponding communication strategy.

For the optimal configuration of building space utilization, the general idea of the particle swarm optimization algorithm is to divide the overall optimization configuration task into multiple sub tasks according to the region for simultaneous implementation, that is, the particle swarm is divided into multiple sub populations, and each sub group can perform the optimization task independently. In the process of independent optimization, each sub group will communicate in time to share the best configuration scheme location. In order to reduce the cost and time consumption, the author uses the coarse grain parallel model to build the optimal allocation model of building space utilization [18]. The master-slave parallel algorithm framework is shown in Figure 3.3. The algorithm includes master node and slave node. When there is a task, the master node will decompose and distribute the task to each slave node, and communicate with the slave node in a timely manner. The slave node is responsible for completing the assigned tasks and maintaining communication with the master node. Because the master node does not participate in the task execution, the parallel efficiency is wasted. At the same time, the slave nodes cannot communicate directly, which increases the communication workload of the master node, and the communication efficiency is low. The point-to-point parallel algorithm framework is shown in Figure 3.4. This form discards the distinction between master and slave nodes, and each node can directly communicate with each other, which improves the communication efficiency. However, when the number of nodes is large, the communication network is complex. According to the above two parallel forms, the author proposes a chain parallel structure, as shown in Figure 3.5. The chained parallel architecture has multiple master nodes to allocate tasks, while maintaining communication with slave nodes and other master nodes. Slave nodes belonging to the same master node can directly communicate with each other to improve communication efficiency [7, 17].

4. Result Analysis.

4.1. Simulation test and verification. In view of whether the building space utilization optimization algorithm based on spatialized particle swarm optimization proposed by the author can be applied to the building space configuration problem of multiple regional scales, the author uses three regions to test and verify.

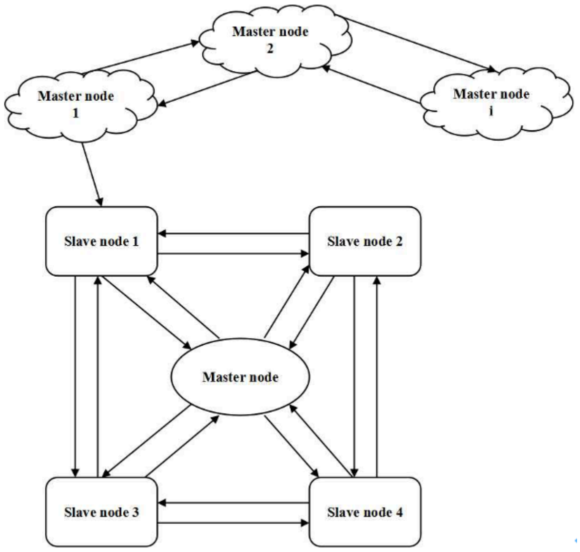

Fig. 3.5: Structure of chained parallel algorithm

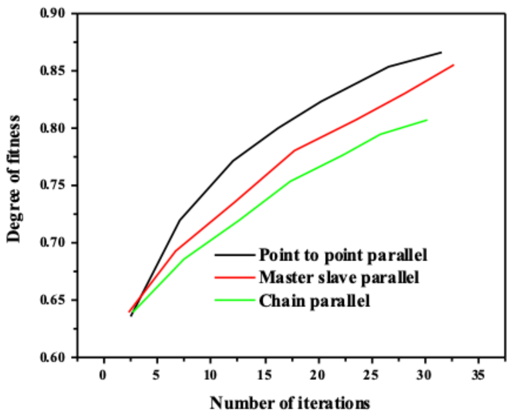

Fig. 4.1: Fitness comparison of three parallel models with different iterations

The experimental data is based on the utilization of building space in these three regions in 2015, the vector map is divided into 30 m×30 m sized grids, and all statistical data and spatial data are projected on each grid cell. The author tested the convergence speed and running time of the spatialized particle swarm optimization parallel algorithm.

To verify the validity of the proposed chain parallel architecture, we compare it with the master-slave parallel structure and the point to point parallel structure [15, 19]. Figure 4.1 shows the fitness convergence curves of the three parallel models under five process parallelism. It can be seen from Figure 4.1 that the difference between the fitness values of the final convergence of the three parallel models is small, and the main difference is the convergence speed. The convergence speed of the chained parallel model proposed by the author is obviously better than that of the master-slave model and the point-to-point model.

During the run time test, set the three parallel models to run under the conditions of 8, 16, 32 and 64 nodes respectively, and the results are shown in Table 4.1 [8, 1]. Because of the combination of the advantages of master-slave model and point-to-point model, the running time of chained parallel model is significantly lower

Table 4.1: Running time of three parallel models/s

Model type	8 nodes	16 nodes	32 nodes	64 nodes
Chain type	143	86	43	31
Master-slave	184	112	76	47
Point to point	156	98	78	93

than that of the other two parallel models. Especially when the number of nodes is large, the setting of multiple master nodes can allocate tasks with greater degrees of freedom without increasing too much communication burden.

5. Conclusion. The optimum model of indoor space utilization was established by PSO. Based on the number of buildings and the total area, this paper makes a general improvement on the PSO algorithm, and defines some relative optimization strategies. The symbol coding method is used for spatial coding, the maximum standardization method is used for data processing, and the influencing factors of space utilization are summarized to obtain the objective function of the optimal configuration of building space. The advantages and disadvantages of master-slave parallel model and point-to-point parallel model are analyzed, and the optimization algorithm of chain parallel structure is proposed. The data simulation test results show that the optimization algorithm proposed by the author has good performance and can meet the conventional optimization requirements of building space utilization.

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