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# *Smart Scheduling and Resource Allocation Algorithms in Digital Twin Campus*

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***Abstract:*** With the deepening application of digital twin technology in various fields, campus management has also ushered in a new change. This paper focuses on the research of intelligent scheduling and resource allocation algorithms in digital twin campus. First, the basic concept of digital twin technology and its application scenarios in campus are introduced. Second, a campus resource optimization model based on intelligent scheduling algorithm is proposed, and the scheduling efficiency and resource utilization are improved through multi-objective optimization and data-driven decision-making mechanism. In addition, allocation algorithms applicable to a wide range of campus resources are designed, and their automated applications in dynamic environments are explored. Through simulation and experimental verification, the algorithms proposed in this paper show significant advantages in improving the efficiency of campus resource management. Finally, this paper summarizes the research results and looks forward to the development direction of digital twin campus in the future.

## 1. Introduction

With the rapid development of IoT, cloud computing and big data technologies, digital twin technology is gradually becoming a key tool in modern campus management[1]. By constructing a virtual mirror of the physical campus, the digital twin campus realizes real-time monitoring and management of campus facilities, personnel activities and resource allocation[2]. This technology not only improves the efficiency of campus management, but also lays the foundation for realizing an intelligent and automated management model[3].

With the expansion of campus scale and diversification of management needs, how to efficiently schedule campus resources and optimize resource utilization in digital twin systems has become an urgent problem[4]. The introduction of intelligent scheduling and resource allocation algorithms provides a new solution to this challenge[5]. Intelligent scheduling algorithms can dynamically adjust the use of resources based on real-time data to ensure efficient allocation of teaching, research and living resources[6]. Meanwhile, the resource allocation algorithm further optimizes the use of resources to avoid waste and overuse of resources. Linear Programming Objective Function:

$$\text{Maximize } Z = c_1x_1 + c_2x_2 + \cdots + c_nx_n \tag{1}$$

The purpose of this paper is to study the intelligent scheduling and resource allocation algorithms in the digital twin campus, and to improve the intelligence of campus management by constructing a data-driven scheduling model and resource allocation mechanism. The article will first introduce the digital twin technology and its application background in campus, then discuss the design and optimization of intelligent scheduling algorithm and resource allocation algorithm, and finally verify the effectiveness of the algorithms through simulation experiments and look forward to the future development direction.

## 2. Digital Twin Campus Overview

Digital twin technology originated in the manufacturing industry, which monitors and analyzes the state and behavior of physical entities in real time by creating virtual models of them[7]. In recent years, with the rapid development of IoT, big data and artificial intelligence technologies, digital twin technology has gradually expanded to other fields, such as urban management, healthcare and education[8]. In campus management, digital twin technology realizes all-round monitoring and management of facilities, environment and personnel on campus by establishing a digital mirror of the virtual campus, showed in Fig.1.

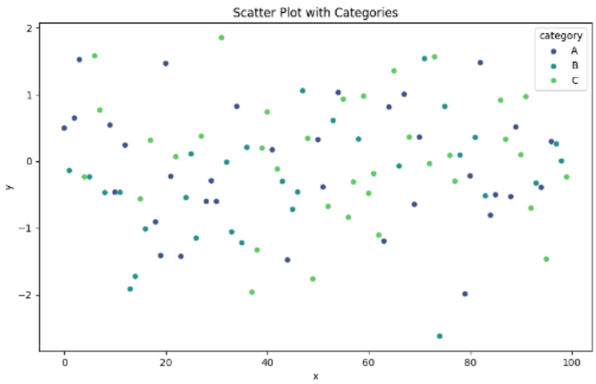


Figure 1: Scatter Plot with Categories

There are a wide range of application scenarios for digital twin technology in the campus environment[9]. By monitoring the building facilities, energy consumption, and environmental quality of the campus in real time, administrators are able to keep abreast of the operational status of the campus[10]. For example, the digital twin system can monitor the use of classrooms, so as to rationally arrange teaching resources; it can also optimize the energy consumption in the campus and realize intelligent energy management. In addition, by analyzing the movement of people and the use of equipment on campus, digital twin technology can also improve the efficiency of security management and ensure campus safety, Constraints in Linear Programming:

$$\begin{aligned} a_{11}x_1 + a_{12}x_2 + \cdots + a_{1n}x_n \le b_1 \\ a_{21}x_1 + a_{22}x_2 + \cdots + a_{2n}x_n \le b_2 \\ a_{m1}x_1 + a_{m2}x_2 + \cdots + a_{mn}x_n \le b_m \end{aligned} \tag{2}$$

The strength of the digital twin campus lies in its powerful data collection and analytics capabilities, which can provide accurate decision support through seamless integration with the physical campus. This technology not only improves the efficiency of resource utilization, but also predicts and prevents potential problems through a data-driven approach. For example, digital twin technology can predict the risk of equipment failure and perform maintenance in advance to avoid unexpected situations. In addition, digital twin campuses are also highly scalable, enabling the gradual addition of functional modules based on actual demand to accommodate future management needs.

Despite the promising applications of digital twin campuses, the current application of the technology faces a number of challenges[11]. For example, real-time and accuracy of data is still a key issue for digital twin systems, and lagging or incorrect data may lead to poor decision-making. In addition, how to extract valuable information from massive data and protect data privacy and security are also challenges that need to be addressed[12]. Finally, the construction and maintenance of a digital twin campus requires a lot of financial and technical support, which is a considerable challenge for schools with limited resources.

## 3. Intelligent Scheduling Algorithm

In the digital twin campus, the intelligent scheduling algorithm plays a crucial role to ensure the efficient use of resources and optimization of campus management through the reasonable allocation and real-time adjustment of all kinds of resources in the campus. This paper will discuss the design and application of intelligent scheduling algorithms from three aspects: firstly, the basic principles of intelligent scheduling algorithms are introduced, then the intelligent scheduling model applicable to campus scenarios is constructed, and finally the optimization method and practical implementation of scheduling algorithms are discussed. These three parts of the content will systematically illustrate the specific applications and challenges of intelligent scheduling in the digital twin campus.

### 3.1 Fundamentals of Intelligent Scheduling Algorithms

Intelligent scheduling algorithm is an algorithm that utilizes computer science and artificial intelligence technology to automate task allocation and resource scheduling. It dynamically adjusts the resource allocation scheme by monitoring the current state of the system in real time and combining it with a predetermined objective function to optimize the overall system performance. In the digital twin campus, the intelligent scheduling algorithm can be applied to a variety of areas such as classroom allocation, equipment use, personnel scheduling, etc., to ensure that campus resources are utilized in the most effective way, showed in Fig.2.

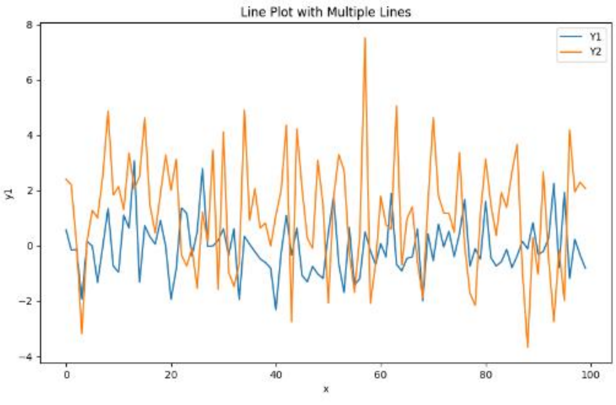


Figure 2: Line Plot with Multiple Lines

Heuristic algorithms are a class of rule-of-thumb based optimization algorithms commonly used to solve complex scheduling problems. In intelligent scheduling, heuristic algorithms quickly generate better solutions by utilizing domain knowledge. For example, simulated annealing algorithms and forbidden search algorithms can find near-optimal resource allocation solutions in a large search space. Although heuristic algorithms are not guaranteed to find a globally optimal solution, they are able to provide high-quality scheduling results in a reasonable amount of time, which is particularly suitable for scenarios with high real-time requirements in digital twin campuses.

Genetic algorithm is a search algorithm that simulates the natural evolutionary process and is particularly suitable for solving multi-objective optimization problems. In intelligent scheduling, genetic algorithms gradually evolve optimal or near-optimal scheduling schemes through operations such as selection, crossover and mutation. For example, genetic algorithms can be used to optimize classroom scheduling arrangements, balance the demands of different courses, and maximize the utilization of teaching resources. The parallelism of genetic algorithms also makes them very suitable for dealing with large-scale complex scheduling problems, and they have a wide range of application prospects in digital twin campuses. Simulated Annealing Cost Function:

$$E(T) = E_0 + \alpha \cdot \ln\left(\frac{T}{T_0}\right) \tag{3}$$

With the continuous development of data-driven technology, machine learning is gradually becoming an important part of intelligent scheduling algorithms. By learning from historical data, machine learning algorithms can predict resource demand trends and optimize scheduling in advance. In the digital twin campus, intelligent scheduling algorithms combined with machine learning can adaptively adjust scheduling strategies to the dynamically changing campus environment. For example, by predicting classroom usage, the system can schedule classroom resources in advance to avoid idle or overused resources. This data-driven scheduling greatly improves the intelligence of the algorithm. machine learning models can analyze past classroom utilization data to forecast future occupancy trends. This enables the system to proactively allocate classrooms based on anticipated needs, minimizing instances of both underutilization and overbooking. Additionally, machine learning can refine scheduling strategies in real time by continuously learning from new data, thus adjusting to unexpected changes and optimizing resource allocation on-the-fly. This adaptive approach enhances the efficiency and effectiveness of scheduling processes, ensuring that resources are used to their fullest potential while maintaining flexibility to accommodate evolving requirements. Consequently, the incorporation of machine learning into scheduling algorithms not only elevates their intelligence but also transforms resource management into a more responsive and strategic endeavor. Genetic Algorithm Fitness Function:

$$f(x) = \frac{1}{1+\mathrm{Cost}(x)} \tag{4}$$

### 3.2 Intelligent Scheduling Model Construction for Campus Resources

The Intelligent Scheduling Model for Campus Resources aims to optimize the management of campus resources such as classrooms, equipment, and personnel through a systematic approach. The basic framework consists of four main parts: data collection, demand prediction, scheduling decision and execution feedback. First, the utilization data of campus resources are collected in real time through digital twin technology to establish the basic data set for resource management. Then, the demand forecasting model is utilized to predict future resource demand trends and provide a basis for scheduling decisions. Next, based on the prediction results and actual demand, the intelligent scheduling system generates an optimized scheduling plan, and finally continuously adjusts and optimizes the scheduling strategy through the feedback mechanism.

Demand forecasting is a key component in resource scheduling models, which predicts future resource demand by analyzing historical data and real-time information. Commonly used demand forecasting methods include time series analysis, regression analysis and machine learning models. Time series analysis methods are suitable for cyclical demand forecasting, such as classroom utilization; regression analysis can handle demand forecasting related to multiple factors; and machine learning models can combine multi-dimensional data for more accurate forecasting. In a digital twin campus, demand forecasting not only helps improve scheduling accuracy, but also identifies resource shortages or surpluses in advance for timely adjustments.

Scheduling decision-making algorithms are the core part of transforming predicted demand into specific scheduling plans. Commonly used scheduling algorithms include optimization algorithms, heuristic algorithms and hybrid algorithms. Optimization algorithms, such as linear programming and integer programming, can solve the exact optimal solution, but the computational complexity is high; heuristic algorithms, such as genetic algorithms and simulated annealing algorithms, are suitable for dealing with complex scheduling problems, and they can quickly find a near-optimal solution. In campus resource scheduling, appropriate scheduling decision algorithms are selected according to different application scenarios and demands to ensure the effectiveness and operability of the scheduling solution, showed in Fig.3.

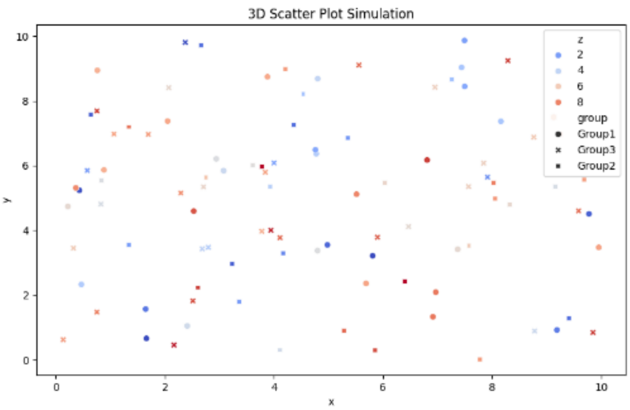


Figure 3: 3D Scatter Plot Simulation

The execution and feedback mechanism is a crucial part of the intelligent scheduling model, which ensures the actual effect of the scheduling scheme and provides the basis for model optimization. In the execution phase, the scheduling scheme is implemented into the actual operation by the system automatically or through manual intervention. In the feedback phase, the system monitors the actual implementation, compares it with the goals of the forecasting and decision-making phases, and collects feedback data to evaluate the scheduling effectiveness. This feedback data is used to adjust the scheduling strategy, optimize the model parameters, and improve the performance of the scheduling system. Through the continuous execution and feedback loop, the intelligent scheduling system can adapt to the dynamic changes in the campus environment and maintain the efficiency and flexibility of resource scheduling.

### 3.3 Optimization and Implementation of Scheduling Algorithms

Scheduling algorithms are optimized to increase resource utilization efficiency, reduce scheduling costs, and improve user satisfaction. In a digital twin campus, the optimization objectives include maximizing classroom and device utilization, minimizing resource idle time, and improving scheduling responsiveness. To achieve these objectives, various optimization strategies can be used, such as adjusting the weights of the objective function, introducing dynamic constraints, and parameter settings of the optimization algorithm. By precisely adjusting the optimization objectives and strategies, the performance of the scheduling algorithm can be significantly improved to better adapt to the complex demands of real applications, showed in Fig.4.

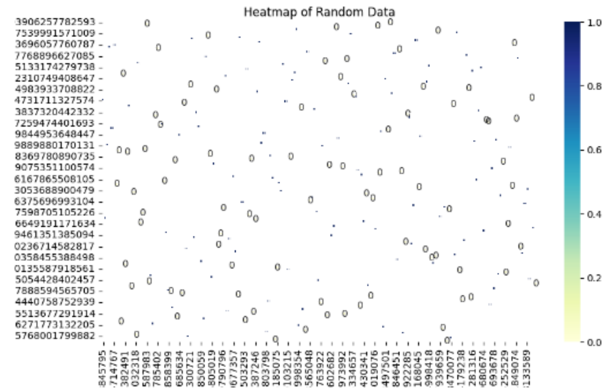


Figure 4: Heatmap of Random Data

Scheduling algorithm optimization techniques include algorithm improvement and parameter tuning. Algorithm improvement usually involves enhancements to existing algorithms, such as the introduction of local search, improved heuristics, or mixing the advantages of different algorithms. Parameter tuning, on the other hand, is performed by adjusting the control parameters of the algorithms, such as crossover and mutation rates in genetic algorithms, and cooling strategies in simulated annealing algorithms, in order to improve the algorithm's search efficiency and solution quality. In addition, adaptive algorithms can be used to dynamically optimize the scheduling process by learning and adjusting strategies online. Selecting appropriate optimization techniques helps to improve the effectiveness and stability of scheduling algorithms in practical applications. Time Series Forecasting Model (ARIMA):

$$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + \cdots + \phi_p X_{t-p} + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \cdots + \theta_q \epsilon_{t-q} + \epsilon_t \quad (5)$$

The implementation of scheduling algorithms involves translating the optimization algorithms into actual runnable programs and integrating them into the management system of the digital twin campus. Common implementation methods include writing custom algorithm code, leveraging existing libraries of optimization tools, and integrating commercial scheduling software. Programming languages such as Python, Java, and C++ are widely used for scheduling algorithm implementation, with Python being a popular choice due to its rich scientific computing library and ease of use. Tool libraries such as SciPy, Gurobi and IBM CPLEX provide powerful optimization features that can simplify the algorithm development process. Scheduling algorithms can be efficiently applied to real systems by choosing and configuring implementation methods and tools appropriately. Resource Allocation Model:

$$R_i = \frac{\text{Demand}_i}{\text{Supply}_i} \quad (6)$$

The validation and tuning of scheduling algorithms is an important step to ensure that the algorithms operate effectively in real-world environments. The validation process usually consists of simulation experiments and real-world deployments to evaluate the performance of the algorithm by comparing it with benchmark data and expected results. Simulation experiments can help identify problems with the algorithm in specific scenarios, while actual deployments provide feedback data in real environments. Based on the validation results, the algorithm parameters are adjusted, the algorithm design is improved, or the implementation details are modified to solve the identified problems and improve the adaptability of the algorithm. Through continuous validation and adjustment, we ensure that the scheduling algorithm is optimized for application in digital twin campuses.

## 4. Design and Application of Resource Allocation Algorithms

The design principles of resource allocation algorithms include fairness, efficiency and flexibility. Fairness refers to ensuring that each demand side can obtain a reasonable share of resources in the resource allocation process; efficiency requires that the algorithm can maximize the utilization rate of resources and reduce idle and wasteful resources; and flexibility emphasizes that the algorithm can adapt to dynamically changing demands and environments. In the digital twin campus, when designing the resource allocation algorithm, it is necessary to comprehensively consider the resource needs of teaching, research and life, and design an allocation strategy that satisfies the needs of all parties according to different priorities and constraints, showed in Fig.5.

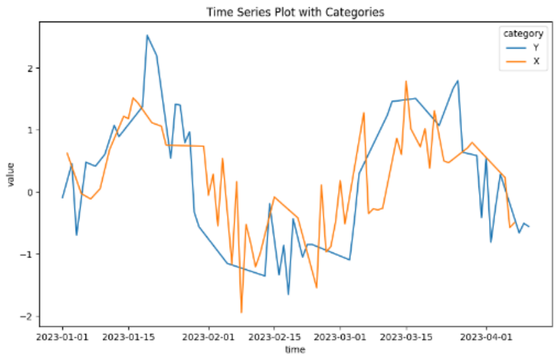


Figure 5: Time Series Plot with Categories

Static resource allocation policies are usually based on fixed demand and resource allocation, such as scheduling classroom and equipment usage according to a fixed schedule. This type of strategy is suitable for scenarios with small changes in demand, and achieves efficient use of resources by optimizing the resource allocation schedule. For example, scheduling classroom and lab usage according to the schedule at the beginning of the semester can effectively avoid resource conflicts and wastage. The advantage of the static resource allocation strategy is its simplicity and intuition, but it lacks the ability to adapt to real-time changes, so it is usually applicable to situations where the demand is stable or changes less.

The dynamic resource allocation strategy adapts to changing demands and environments by monitoring and adjusting resource allocation in real time. The strategy utilizes real-time data provided by the digital twin to dynamically adjust the resource allocation scheme in response to unexpected needs and environmental changes. For example, the scheduling of teaching activities or the prioritization of equipment usage is dynamically adjusted based on real-time classroom usage and equipment status. The key to the dynamic resource allocation strategy lies in the real-time and adaptive capabilities of the algorithm, which can better cope with uncertainty and change and improve the flexibility and efficiency of resource utilization.

Application cases of resource allocation algorithms in digital twin campuses include classroom scheduling, equipment management, and staff scheduling. For example, by applying dynamic resource allocation algorithms, real-time scheduling of classrooms is carried out to cope with changes in course scheduling and temporary demands; or optimization algorithms are used to allocate resources to laboratory equipment to ensure rational use of experimental resources. In addition, the resource allocation algorithm based on predictive data can also pre-allocate resources at the beginning of the semester to prepare in advance. Through these application cases, the effectiveness and advantages of resource allocation algorithms in actual campus management can be verified, and empirical evidence can be provided for further optimization.

## 5. Conclusion

This paper discusses the intelligent scheduling and resource allocation algorithm in the digital twin campus, which significantly improves the efficiency of campus management and resource utilization by constructing an intelligent scheduling model and resource allocation strategy. The optimization and implementation of the intelligent scheduling algorithm achieves dynamic management and efficient allocation of campus resources by introducing heuristic algorithms, genetic algorithms and machine learning techniques. The design and application of the resource allocation algorithm, combining static and dynamic strategies, effectively solves the challenges brought by resource idleness and demand changes.

The combination of digital twin technology with intelligent scheduling and resource allocation algorithms not only improves the automation level of campus management, but also optimizes the allocation of resources, making the campus environment smarter and more efficient. However, with the continuous development of campus management requirements, the existing algorithms and models still need to be further optimized to cope with more complex and dynamic management challenges. Future research can focus on the adaptive enhancement of algorithms, in-depth analysis of real-time data, and implementation strategies for large-scale applications to further promote the development and application of digital twin campus technology. The intelligent scheduling and resource allocation algorithm in digital twin campus provides an innovative solution for modern campus management, which has a broad application prospect and development potential. By continuously optimizing the algorithms and systems, a more intelligent campus management mode can be achieved in the future, improving the overall management level and resource use efficiency.

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