Design and Simulation Research on Digital Twin Task Driven Dynamic Control Model for Manufacturing Enterprises

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This article proposes a task driven dynamic operation management model based on digital twin technology from the perspective of manufacturing enterprises adapting to complex and diverse environments to improve management performance. It comprehensively utilizes various methods of information collection and fusion, real-time status response feedback control, and task priority sorting to achieve a dynamic optimal structure that supports collaboration of multiple task operations. By using Anylogic multi-agent simulation tool to model and simulate the model, multiple typical scenarios for task execution were set, and the model was evaluated for resource utilization, response time delay, and task scheduling quality. The experimental results showed that the model in this paper can effectively improve task execution efficiency (by 12.4%), task resource allocation and matching degree (by 17.8%), and task response timeliness (by an average time reduction of 23.5%), which can meet the requirements of intelligent production and business management.

Povzetek: Članek predstavi dinamični kontrolni model na osnovi digitalnega dvojčka za proizvodna podjetja, z združevanjem podatkov, povratnim krmiljenjem in razvrščanjem prioritet. Simulacije v AnyLogicu izboljšajo učinkovitost, ujemanje virov ter skrajšajo odzivni čas.

1 Introduction

Against the backdrop of increasingly complex manufacturing systems, traditional information systems lack dynamic perception and flexible scheduling mechanisms, making it difficult to meet the production demands of high-frequency changes and resource heterogeneity. Manufacturing enterprise information systems must transform from static process support to dynamic feedback regulation, achieving task driven structural optimization and cross module linkage.

This type of system is no longer just an information recording tool, but has become a master control structure that integrates state perception, process simulation, and feedback optimization. Research has shown that digital twin models can dynamically reconstruct multi task execution nodes while maintaining real-time performance, significantly improving execution efficiency and resource utilization levels. Cao M et al. found that digital twin technology can increase the average return on investment by 15% and decision-making efficiency by 20% in manufacturing enterprises, resulting in operational benefits [1].

In terms of path generation and scheduling accuracy, Li R et al. used mobile robots as experimental objects to construct a dynamic digital twin system, and achieved model adaptive adjustment through neural network methods, improving obstacle avoidance ability by 18%, further verifying the feasibility of the twin system's response to dynamic environments [2]. From the perspective of global deployment experience, Huang Z studied the application of digital twin driven robot systems in intelligent manufacturing and pointed out that the system deployment strategy needs to dynamically adjust model parameters and collaborative mechanisms according to the production environment to achieve efficient operation [3].

The dynamic operation and control model constructed by our research institute is dedicated to bridging the closed-loop relationship between state perception, path inference, and scheduling execution in information systems. The overall model includes three core mechanisms: task structure diagram generation, feedback-based path reconstruction mechanism, and digital twin integration platform. Compared to the traditional scheduling process's time triggered structure, this model focuses on state feedback and has the ability to adaptively adjust paths and fuse multiple sources of information, which can improve the accuracy of information response and operational coherence under complex tasks. The model construction relies on knowledge graphs for semantic modeling of task nodes, and dynamically adjusts the execution path using feedback state sets to form a flexible and coupled scheduling framework.

On the one hand, recent AI research has also provided support for semantic construction and scheduling generation of dynamic models. Genc O conducted an experiment on industrial task automation generation based on a large language model, and the results showed that the AI model can assist in building an industrial task chain with complete semantic logic and reasonable reasoning paths. The consistency between its generation quality and expert modeling results exceeded 87% [4].

Wang J et al. proposed a spindle digital twin model based on deep residual networks for device modeling and high-frequency state prediction. The model has an accuracy of up to 98.17% and can maintain stable operation under complex loads and abnormal disturbances, verifying the applicability of the three-layer twin structure in high-frequency state mapping scenarios [5].

On the other hand, the overall structure of the digital twin model should have the ability to integrate across systems and adapt to task scenarios. Shen et al. proposed that by integrating the Internet of Things and digital twin technology, intelligent management of urban underground pipe gallery systems can be achieved, emphasizing the key role of information interconnection and data flow in complex system collaboration [6]. This provides important reference for interface management and platform compatibility design in the deployment phase of our research model.

Unlike most current digital twin architectures that only consider optimization based on static scheduling or partial feedback control, the pattern proposed in this paper based on the "task resource configuration relationship graph" and "multi node dynamic rule optimization strategy" is more capable of synchronously completing dynamic scheduling in a short period of time, compatible with experiments in Python and AnyLogic simulation environments, and has stronger scalability. It not only exceeds the limitations of existing digital twin architecture models in terms of functional configuration, but also demonstrates better dynamic scheduling response performance through actual comparative testing, reflecting the contribution of this study to new architecture design and corresponding performance optimization at the existing digital twin application level.

In summary, this study will construct a dynamic operation and control model based on digital twins, and carry out system design around task structure generation, The goal of the model is to achieve a synergistic improvement in real-time, autonomy, and adaptability of manufacturing enterprise information systems, breaking through the dependence of traditional scheduling strategies on pre-set paths and static resource binding, and promoting enterprises to move from "process execution based information systems" to "state driven intelligent systems".

2 Related work

The construction process of manufacturing enterprise information systems has long relied on static rule driven and pre-set process control models. Although it has the advantage of consistent plan execution under traditional stable working conditions, especially in situations such as multitasking concurrency, resource sharing conflicts, and rapid process switching, existing system paths are rigid, state perception is slow, and abnormal response is insufficient, making it difficult to support the high dynamic complexity of production sites. Luo et al. proposed a hybrid digital twin architecture for discrete manufacturing, which combines physical modeling and data-driven methods to significantly improve the real-time and accuracy of device predictive maintenance [7],On the one hand, continuous collection of equipment data, job status, environmental parameters, and human-machine interaction data at the manufacturing site has been achieved, and the system has the basic conditions to build a real-time status view. However, traditional information systems still adopt a plan driven mechanism based on master data and historical records, resulting in a lack of state feedback and a fragmented scheduling chain, which cannot support dynamic optimization of scheduling strategies. On the other hand, the internal process logic and task structure of the system often adopt static configuration methods, lacking expression mechanisms for complex dependency relationships and task evolution states. Yue C et al. proposed a twin based prediction framework [8].

To solve this problem, it is necessary to build a technical framework that includes state awareness, dynamic path optimization, task linkage, and path feedback information processing functions. And digital twin technology can build real-time traceable models in a timely manner, and achieve dynamic modeling of task processes and path re planning through logical models. At the same time, a "perception modeling correction execution" control chain is implemented for scheduling feedback, which automatically responds to and dynamically updates various abnormal situations, improving scheduling stability and load capacity.

In order to better demonstrate the fundamental structural differences between traditional information systems and digital twin systems, this study summarizes the differences in data mechanisms, scheduling mechanisms, feedback mechanisms, and other seven aspects between traditional information systems and digital twin systems, as shown in Table 1.

Table 1 : Comparison of evolution characteristics of information system scheduling mechanisms in manufacturing enterprises

Comparing dimensions	Traditional Information Systems	Digital twin driven information system	Difference focus
Data collection mechanism	Based on static master data and regular uploads	Real time perception and multi-source data fusion	Real time and accuracy of data
Model driven structure	Fixed rule model, static binding of processes	State driven model, virtual real collaborative evolution	The dynamism of scheduling logic
Path generation method	Single planning, manual intervention and adjustment	Continuous optimization, automatic triggering of refactoring	Refactoring ability and feedback timeliness
Multi task coordination mechanism	Parallel execution, weak dependencies, task fragmentation	Node linkage, strong dependency, graph collaboration	Ability to express task structure
Abnormal response strategy	Manual interruption or process jump	Simulation prediction+adaptive path replanning	System robustness and recovery mechanism
Control and Feedback Structure	Unidirectional control+passive recording	Closed loop linkage+intelligent adjustment	Perform chain integrity
Applicable scenario types	Stable production with minimal process changes	High dynamic tasks, multi-source constrained environment	System adaptability and scene breadth

From the table, it can be seen that traditional systems mainly rely on static master data and preset rules, lacking real-time state perception and adaptive scheduling path capabilities. Their control chain is usually one-way triggering, task fragmentation, and feedback lag. The digital twin system is based on state perception for scheduling, and achieves dynamic path generation and multi task dependency recognition through graph linkage between task nodes. It can automatically respond to abnormal changes and continuously optimize resource allocation, achieving true full process flexibility and system level self-regulation. Especially in manufacturing scenarios with high change frequency and complex constraints coexisting, digital twin systems exhibit stronger stability and adaptability.

Although some systems have attempted to introduce edge collection devices and status visualization platforms, without structured model support, their data still cannot effectively enter the scheduling logic core. Therefore, relying solely on state collection is not enough to form a closed-loop mechanism. Information systems must build a unified semantic modeling structure and feedback control architecture around digital twins, transforming multi-source data into intrinsic drivers for task logic and path scheduling, and achieving a truly state led operating mode.Huang J constructed a dynamic scheduling framework based on reinforcement learning to achieve intelligent decision optimization of manufacturing systems driven by digital twins, highlighting its collaborative value in state perception and resource allocation [9].

The communication and synchronization method of the digital twin system proposed in this article adopts a real-time data communication structure based on WebSocket platform, which realizes the interconnection between various components; Real time collection and format normalization of data from sensors and action units through a central platform for distribution and forwarding; Using asynchronous event driven approach to continuously synchronize task status, resource occupancy status, and scheduling feedback status; During the communication process, real-time data

communication and low latency are ensured through timestamp and latency detection.

In summary, the future evolution direction of manufacturing enterprise information systems is not only the expansion of system functions, but also the deep reconstruction of operating paradigms. Digital twin technology should serve as an embedded logic in the system scheduling structure rather than a peripheral visual layer, playing a central role in state recognition, path generation, feedback control, and anomaly recovery.

3 Suggested control plans

3.1 Digital twin

This article focuses on the problems of "scheduling lag and policy lag" in the system, and will mainly study the matching of tasks and resources, as well as the principles of interaction between multiple nodes, in order to achieve the goal of flexible task control and workflow control. The quality of task execution time and system response in the workflow model will be tested. To this end, a modular modeling approach will be adopted and simulated comparative experiments will be conducted in combination with actual situations to verify the optimization of important parameters in the model.

In order to increase the reproducibility of the research conducted, this paper adopts a multi-agent simulation method, starting from various resource units, workflows, and control components in the enterprise, and uses a modular construction form to build a dynamic operation management model on the AnyLogic8.7 platform. In the simulation process of this article, different types of tasks and resource allocation were used, and the focus of the scheduling process was on event triggering and changes in resource status. Improved A * algorithm and load balancing strategy were used to generate routes. Add real-time information exchange function to WebSocket and Kafka, and send task commands and collect status through Python and Flask interfaces. The model indicators are represented by parameters such as task runtime, resource utilization, and response speed, and ablation experiments are conducted to further demonstrate the applicability and robustness of the model in complex situations.

To ensure the reproducibility of the research, the research process is as follows: AnyLogic8.7 is used as the research environment and modeling tool, and a multi-agent modeling approach is adopted to modularize the resource nodes, task processes, and controllers; Set tasks with different categories and corresponding resource allocation situations, with task triggering and resource status changes as the main scheduling principles; Combining the improved A * path search algorithm with load priority strategy as dynamic routing planning; Using WebSocket and Kafka technologies to implement system data exchange functions, as well as Python and Flask languages to implement command execution and state synchronization functions; Propose evaluation indicators such as task completion time, resource utilization, and response speed to measure system performance, and conduct ablation experiments to verify the impact of key mechanisms and system stability.

In the process of manufacturing enterprise information systems moving towards dynamic operation and intelligent control, digital twin technology constitutes the fundamental support for system structure reconstruction and mechanism transformation. Its essence is to build a virtual model system that is real-time mapped, state equivalent, and behavior synchronized with the physical production system. With the help of this model, it can achieve predictive simulation of the production process, dynamic planning of task paths, and intelligent scheduling of resource states.Shen B proposed an edge cloud collaborative digital twin architecture for real-time industrial process control, emphasizing the advantages of distributed architecture in improving system response speed and control accuracy [10].Under this framework, the information systems of manufacturing enterprises no longer rely on fixed plans and static models, but instead build a closed-loop logic of task control and scheduling response around "real-time status+virtual real linkage".

The digital twin system mainly consists of four key components: physical entities, virtual models, data channels, and feedback strategies. Among them, physical entities undertake the execution of real production tasks; Virtual models are based on modeling semantics, reconstructing device structure, workflow, and resource logic; The data channel connects the physical and virtual worlds, enabling real-time state collection, event flow transmission, and prediction information feedback; The feedback strategy generates scheduling adjustments and path reconstruction schemes based on the state evolution and behavior simulation results of the twin body, thereby constructing a complete control feedback mechanism.

In terms of modeling logic, digital twins map various states in manufacturing systems into a unified vector representation, and introduce mapping functions to achieve real-time transformation of system behavior. If the state variable of the physical system is $S(t)$ and the state representation of the digital twin system is $S_d(t)$, then its virtual real synchronization relationship can be expressed as:

$$S_d(t) = f_{map}(S_p(t), \Delta t, \theta) \quad (1)$$

Among them, f_{map} represents the state mapping function, Δt is the sampling period, and θ is the system noise and sensing deviation parameters. This mapping mechanism ensures that the state of the virtual system can be continuously updated and approach the real process, thereby supporting the dynamic calculation of task scheduling logic.

n the scheduling mechanism, the digital twin system utilizes its ability to grasp equipment status, process progress, and resource load to drive the generation and update of execution paths. The path generation logic is based on task queueT={t1,t2,tn}and resource set R={r1,r2,rn}, introducing constraint function $C(t_i, r_j)$ and state function $S_d(t)$ to jointly determine the scheduling priority and path topology of tasks. The scheduling driver function can be expressed as:

$$P^*(t) = \arg\min_{p\in\rho} \sum_{i=1}^{n} \left[C(t_i, r_j) + \lambda \cdot \delta(S_d(t), P_i)\right] \quad (2)$$

Among them, $P^*(t)$ Among them, ρ is the set of optional paths, λ is the state deviation penalty coefficient, and δ represents the deviation function between the current state and the expected path. Through this mechanism, the system not only considers traditional resource matching and job order, but also combines the twin state to achieve dynamic path selection and real-time correction.

In addition, digital twin systems have the ability to express structural reconstruction, especially in scenarios where task processes are highly heterogeneous, equipment switching is frequent, and resource bottlenecks are variable. Their virtual modeling structure can support modular expression of process flows, construction of task dependency graphs, and simulation and prediction of abnormal evolution paths, thereby providing highly flexible organizational mechanisms and abnormal response strategies for the system. Gu M et al. pointed out based on typical engineering practices that twin modeling can effectively support the evolution of task structure and control of working condition response[11].Through the "task resource state" ternary mapping structure, twin systems can explicitly model the logical dependencies between task nodes and dynamically adjust the execution order and resource assignment method of nodes when state disturbances occur.

In actual system deployment, digital twin systems typically operate as an intermediate layer of manufacturing information systems, connecting the underlying sensor network with the upper level decision scheduling module. Its input comes from PLC acquisition system, MES platform or edge device nodes, and its output is scheduling control instructions, resource configuration suggestions and execution feedback data. The system achieves high-frequency state synchronization and low latency feedback through an edge cloud collaborative architecture, combined with graph structured data storage and event driven computing, to support joint scheduling requirements for multitasking, multi constraint, and multi-path. Wu J et al. validated the signal generation and driving capabilities of twin models in high fidelity state perception and deep recognition, providing an algorithmic foundation for fault diagnosis and feedback control in complex equipment operation[12].

The focus of this work is to enhance the usability and applicability of digital twin modeling. Therefore, this article adds detailed explanations on system implementation and integration based on this foundation. Among them, the logical information layer of this article is built on MySQL database+Flask interface service, which realizes the maintenance of model parameters and data input functions; The physical entity layer collects real-time data through Siemens PLC and OPCUA protocol, ensuring its accuracy and universality at the information level; The interactive mapping layer uses Node RED repeaters to process data and obtain visualized results, and the connection between layers is also integrated across platforms through RESTful APIs.

The data management system used in this system adopts centralized data services, which uniformly receive data transmitted by devices and perform standardized processing and storage. Using Kafka message queue technology to achieve asynchronous transmission and caching of data. Real time reflection of the correspondence between entities and information is achieved by sampling at regular intervals of 5 seconds and synchronizing marker point matching, using timestamps for correction.

In addition, preliminary integration and real-time interactive verification based on WebSocket have been implemented on the MES system of manufacturing enterprises. The relevant processes and configuration files are provided in the appendix for repeated verification in subsequent research.

In summary, digital twins are not only visual tools for manufacturing systems, but also the core reconstruction platform for information system operation logic and control mechanisms. It demonstrates significant system value in implementing state perception, path scheduling, and execution feedback, providing a modeling foundation, algorithm input, and collaborative interface for dynamic operation and control models. The next section will delve into the structured task nodes supported by this twin system, further elaborating on its structural advantages and scheduling feasibility in multi task management.

3.2 Structured design of task nodes driven by digital twins

Manufacturing tasks exhibit structural complexity, logical dynamism, and resource constraint coupling in actual operation. Traditional information systems that construct task models using fixed flowcharts or linear instruction chains are difficult to effectively support the operational requirements under this multidimensional coupling structure. Yinlun H et al. pointed out that digital twins exhibit unique advantages in addressing complexity and sustainability goals in dynamic decision modeling[13].To address the aforementioned issues, this study proposes a structured design approach for task nodes based on digital twins, which reconstructs the expression paradigm of tasks in information systems and forms a task unit modeling system with state response logic, dependency topology, and resource dynamic binding capabilities.

In this structure, each manufacturing task is defined as a node unit with input states, output goals, resource requirements, and dependency logic, and its executable conditions and operating status are synchronized in real-time by the twin system. Compared to the traditional model where task nodes are unaware of environmental changes and have rigid execution sequences, structured task nodes have three key capabilities: state awareness, path evolution, and multi-source adaptation. They can automatically determine whether activation conditions are met based on task progress, equipment occupancy, and completion of previous processes during actual operation, and trigger the next scheduling logic. Table 2 lists three types of core structural features and briefly explains their representation in digital twin structures.

Table 2：Core structural characteristics of digital twin task nodes

FeatureType	expression	function
State expression	Input/output state mapping	Accurately determine the executable and completion conditions of tasks
Dependency construction	Explicit logical relationship setting	Support task concurrency, mutual exclusion, and conditional triggering
resource mapping	Dynamic resource binding mechanism	Realize real-time scheduling of equipment, manpower, materials, etc

In terms of state expression, the system sets specific startup conditions and expected results for each task node based on perceived data such as equipment status, production progress, and environmental variables, ensuring its real-time and effective execution; In terms of dependency construction, the pre - and post process relationships, synchronous collaboration relationships, and mutually exclusive conditions between tasks are transformed into edge relationships in the graph structure and updated in real-time in the scheduling engine for dynamically generating executable paths; In terms of resource mapping, each task node will bind and allocate based on the current available resource pool when triggered, to avoid delays or deadlocks caused by resource conflicts.

The structured task modeling approach not only improves the accuracy and flexibility of information systems at the task expression level, but also endows scheduling modules with stronger adaptive capabilities. In the case of frequent changes in manufacturing tasks or abnormal nodes, the system can quickly complete task reconstruction and resource reallocation based on the current state graph, effectively shorten response cycles, and improve overall operational efficiency.

From the perspective of system deployment, this modeling approach has been integrated into the core logic of the scheduling engine, and through docking with the data bus of the digital twin platform, it achieves real-time status synchronization, dependency evolution, and execution feedback closed-loop management of task nodes. Hussein M et al. proposed a multi-agent twin architecture to support real-time management of scheduling coupled structures[14].This mechanism clearly expresses the structural coupling relationship between tasks and provides a reliable foundation for path reconstruction, priority adjustment, and bottleneck avoidance strategies.

To enhance the reproducibility of the model, this article provides pseudocode representation of the key processes of task scheduling and path selection. The pseudocode for scheduling strategy is as follows:

```
Input: TaskList, ResourceStatus
For each task in TaskList:
  Evaluate priority = f(task.deadline, task.type)
  Select node = argmin (node.load × distance_to_task)
  Assign task to node
  Update ResourceStatus
End For
```

This algorithm combines task deadlines and resource loads to dynamically calculate scheduling priorities and optimize task path allocation, ensuring that the system has scheduling efficiency and response resilience in high concurrency task environments.

For the convenience of understanding and simulation implementation, the A * optimized pathfinding algorithm is used to complete the task planning path calculation, taking into account the priority ranking of load perception. The path generation module generates a task topology based on the topology structure of the task graph, calculates feasible path schemes based on the distance between task points and resource points and the occupancy rate of existing devices, and provides the optimal path set; Evaluate priority based on task completion deadlines, equipment occupancy rates, etc., in order to achieve scheduling balance and resource scheduling in multiple task scenarios.

The system needs to establish a sliding monitoring window when creating a feedback system to dynamically obtain the execution status of scheduling and task nodes. When abnormal situations such as task failures, task path conflicts, and task resource congestion are detected, the system will provide feedback and use a scheduling engine to dynamically reschedule and reconstruct task distribution.

This scheduling strategy is implemented using Python programming and nested in any AnyLogic interactive interface simulation environment. The operation of work nodes is controlled according to DAG network, which can adapt to changes in working conditions and route changes, making the system have fast adaptability and stable adjustability. It is particularly outstanding in dealing with various problems that arise in complex production processes.

3.3 Dynamic path generation strategy supported by digital twins

The task path in manufacturing systems is not fixed during actual operation, but is dynamically influenced by multiple variables such as equipment status, resource distribution, and task progress rhythm. Fixed flowcharts and rule-based scheduling mechanisms are difficult to respond to frequent disturbances in the production environment, which can lead to process rigidity, node congestion, and resource conflicts. Till B et al. pointed out that unit level twin models can help achieve real-time feedback mechanisms for path control[15].Therefore, this section proposes a path generation strategy based on digital twin support, aiming to build a task execution chain with dynamic evolution and real-time feedback capabilities.

At the beginning of system operation, the scheduling module relies on the structured task model constructed in the previous section to perform semantic analysis and graph construction on all manufacturing tasks, forming a logical framework of executable paths. The task graph serves as the input foundation, abstracting the dependencies, resource requirements constraints, and concurrency triggering conditions between nodes in a unified manner, becoming the structural support for dynamic path generation.

The system synchronously collects the device operating status, current task progress, and resource load data contained in the twin, and inputs them into the path generation module. All data is transmitted in real-time by the sensing end and kept updated with the high-frequency mapping of the physical system, so that the path generation reflects the changes in the real scene at all times.

In the path generation stage, the scheduling engine introduces a combination optimization algorithm based on constraint satisfaction and state driven, performs path combination operations on nodes in the task graph, and generates a set of all feasible paths at the current time point. Each candidate path has a clear sequence of resource calls and task triggers. The system does not immediately issue instructions, but inputs the path set into the path evaluation module for optimization.

The path evaluation module comprehensively scores based on multiple indicator dimensions, such as total task time, concurrency conflict risk, resource redundancy occupancy, and beat stability. To meet the needs of different process stages, the objective function supports custom weight configuration, such as emphasizing execution efficiency for short cycle tasks and resource balance for long process tasks. Finally, the scheduling engine outputs the path plan with the best score and issues the path instructions to the execution module.

During the scheduling and execution process, the twin platform continuously collects feedback information, including task status transitions, node completion times, and resource status changes. If there is an abnormality in the execution of a node, such as device failure or resource unavailability, the system will trigger a path reconstruction mechanism, recalculate the path set based on current feedback information, and replace the current execution path to ensure that the task chain is not interrupted and the scheduling logic is not invalidated. The entire path generation and dynamic response process is shown in Figure 1:

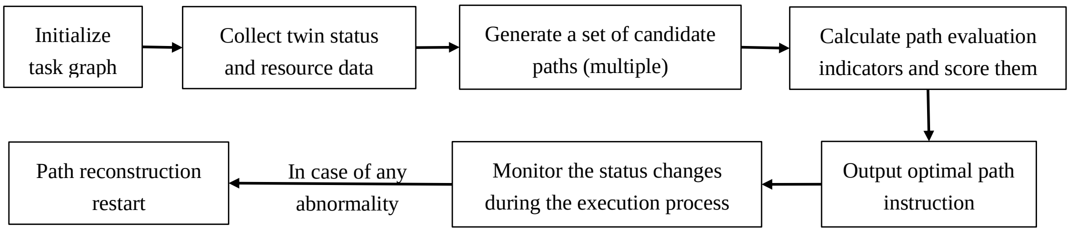

Figure 1：Flow Chart of dynamic path generation

This mechanism realizes the transformation of path planning from static design to dynamic evolution, and has the characteristics of strong structural responsiveness, short feedback cycle, and efficient resource allocation. The scheduling system can maintain path continuity under the conditions of parallel tasks and frequent changes in resource status, effectively improving the execution stability and adaptability of manufacturing enterprise information systems.

3.4 The integrated deployment and collaborative operation mechanism of digital twin models

The deduction of dynamic paths must be transformed into practical instructions and scheduling efficiency through stable model deployment and cross system collaboration. Traditional manufacturing information systems often face difficulties in implementing scheduling strategies due to loose model structures, inconsistent interface standards, and disjointed execution. The introduction of digital twin platforms provides structural support for achieving closed-loop collaboration of "strategy execution feedback". This section focuses on the deployment architecture and feedback mechanism of twin models, and constructs a system collaboration framework for virtual real linkage and real-time updates.

The overall system adopts a hierarchical decoupling structure, including four layers: perception access, twin modeling, scheduling decision-making, and execution feedback. The perception layer collects device, environment, and task data, which are aggregated by the middleware and transmitted to the modeling layer. The scene is reconstructed in the virtual space, and the process state is maintained with structured objects. The decision-making layer runs path generation and scheduling algorithms, outputs strategies to the execution layer, and drives physical devices through PLC units, MES interfaces, and other means.When reviewing the application of digital twins in flexible manufacturing, Kamble S S pointed out that current research mainly focuses on modeling transparency, multi system collaboration, and the construction of real-time closed-loop control mechanisms, providing direction references for future multi scenario collaborative manufacturing [16]. Mihai S. designed a digital twin system based on vehicle terminals, which realizes real-time collaboration and dynamic scheduling of production logistics and workshop operations in manufacturing enterprises, effectively improving the execution efficiency and response capability of workshops [17]..Execute feedback to send data back to update the model, forming a closed loop.

In order to ensure the consistency of the model's operation status, this study introduces a scheduling cycle unified mapping mechanism, which standardizes the system's operation step size to equal time interval T_i ,ompleting state synchronization, path optimization, instruction issuance, and feedback updates within each cycle. The system scheduling iteration can be formalized as:

$$\forall T_i, \exists (S_t, R_t) \Rightarrow S_{t+1} = f(S_t, R_t) \quad (3)$$

Among them, S_t represents the scheduling state vector, which includes task node progress, resource utilization, and load balancing parameters; R_t is the real-time resource status feedback from the twin system; Function f represents the path optimization and strategy generation function. The model can achieve dynamic path reconstruction and node status updates within each time slot, forming a flexible scheduling process that adjusts in real-time with changes in operating conditions.

To avoid scheduling strategy distortion or feedback response delay, the system introduces a multi-layer indicator monitoring mechanism in the feedback mechanism. Set the task completion deviation rate to:

$$\Delta_{task} = \frac{N_{delayed}}{N_{roral}} \quad (4)$$

Among them, $N_{telayed}$ represents the number of tasks delayed in completion within the current cycle, and N_{total} represents the total number of tasks. When the threshold of Δ_{task} exceeds θ, the system will trigger the scheduling correction module to update task priorities or adjust execution paths to ensure stable overall process operation.

At the deployment level, twin modules are integrated into the existing information system in a containerized form, which can run on local edge nodes or cloud platforms, and complete read and write synchronization with underlying devices through standard protocols such as MQTT and OPC-UA. In the pilot verification of an electronic component manufacturing enterprise, the deployment framework achieved parallel deployment without interrupting the existing system. It only took 72 hours to complete the mapping and binding of the entire line of equipment and scheduling modules, and completed 87 path adjustment tasks in the first round of production cycle. The average system response time was controlled within 340ms.

By constructing a collaborative operation chain of "state driven strategy deduction instruction mapping feedback correction", the model proposed in this study has formed a highly coupled control loop in the actual manufacturing process. The model not only has the parallel processing capability for heterogeneous resources and multi task chains, but also can run stably under system disturbances, supporting real-time scheduling and execution control of large-scale complex production tasks, and providing structural support for subsequent result verification chapters.

In order to enhance the repeatability of system deployment, the deployment process is carried out through five technical steps: the first step is to use MQTT protocol to connect with the device sensing equipment and establish a data path; Step 2: Develop a universal modeling approach based on the type of equipment and establish twin models; Step three, start the route scheduler and bind the DAG task flowchart; Step four, deploy feedback detectors, set task termination thresholds, and self recovery options; Ultimately, after the overall operation of the system, the system status is collected at fixed time intervals, road planning is advanced, and action response loops are provided. Every step is recorded in the operation log for future reference, and the configuration options can be changed again to enable other users to quickly repeat this deployment process.

4 Results

4.1 Dataset

This plan is fitted based on the actual manufacturing environment of a discrete manufacturing enterprise, involving five steps: data collection, data preprocessing, learning and validation of scheduling methods, evaluation, and elimination of experiments. The first deployment of sensors collects data on workloads, operational equipment, and surrounding conditions, and converts it into a structured database; The second method involves data preprocessing through temporal matching, diagnosis, and visualization; Thirdly, use the scheduling algorithm proposed in this article to run parallel scheduling 100 times on the same evaluation platform, and set a benchmark model as a reference for verification and evaluation; In order to verify the role of different modules in this model, elimination experiments were specifically set up for three parts: path feedback, state synchronization, and node framework.

To verify the adaptability and scheduling efficiency of the constructed digital twin driven dynamic operation and control model in the actual environment of manufacturing enterprises, this study builds a testing platform based on the real production system of a medium-sized discrete manufacturing enterprise, designs an experimental dataset, and conducts multidimensional performance evaluation. The production process of this enterprise is mainly based on machining assembly, with highly complex process technology, significantly uneven task distribution, and frequent fluctuations in resource allocation. It is a typical representative scenario for testing the dynamic scheduling capability of the model.

The construction of the dataset is based on full chain collection, which collects information covering task execution records, device status data, resource usage, and production cycle parameters through perception terminals deployed on key devices and control nodes. The sensing terminal includes RFID readers, photoelectric sensors, PLC control interfaces, and temperature and humidity detection modules. The sampling frequency is controlled within 1 second per frame to ensure complete recording of dynamic feature changes.

The overall dataset is divided into three types of substructures:

(1) Task flow data: records task numbers, process types, priorities, expected processing times, target production lines, dependencies between previous and subsequent processes, start and end times, etc., forming the basic data unit of the task scheduling graph. The total number of tasks is 1674, distributed among 27 typical product structures, with varying lengths of task chains ranging from 13 levels to 3 levels.

(2) Equipment and resource status data: covering the status identification (running/idle/faulty), current load, historical failure rate, switching time, energy consumption records, and other information of 31 key equipment types (such as CNC milling machines, assembly stations, and detection units) at different time points. The total number of collected records is about 860000, including timestamp alignment and status label annotation.

(3) Production environment and material data: including auxiliary factors such as material inventory status, replenishment cycle, transportation time, processing temperature, and environmental indicators, used to construct multi-objective function input conditions for path evaluation.

All data undergoes preprocessing, including missing value filling, outlier removal, type unification, and time alignment, to ultimately form a structured dataset format, which is integrated into the twin model system in the data center. The dataset structure is shown in Table 3:

Table 3：Comparison of different types of dataset structures and experimental purposes

data type	Number of samples	Sample field	Data update frequency	Application Description
Task flow data	1674 articles	Number, process, sequence, sequence, duration, status, etc	Task generation and update	Building scheduling diagrams and process dependencies
Resource status data	860000 pieces	Equipment number, load, fault, switching time, etc	Sampling per second	Real time feedback on resource allocation and load changes
Environmental and Material Data	21000 pieces	Inventory level, transportation delay, environmental temperature, material type, etc	Updated every 5 minutes	Multi objective path evaluation parameter input

For the classification labels of scheduling tasks, the dataset also marks whether the tasks are delayed, successfully executed, and corresponding path numbers, providing supervisory variables for subsequent model accuracy evaluation. In the process of constructing task dependency graphs, logical dependency relationships are extracted based on the process manual and production BOM table, and a scheduling basic network is established through DAG (Directed Acyclic Graph) structure, enabling the model to have the ability to reconstruct paths for complex task chains.

In addition, in order to simulate the process of abnormal disturbances, 20 sets of experimental data on abnormal disturbances were added to the data, such as sudden facility shutdowns, energy consumption exceeding budgets, material shortages, etc. The occurrence time, end time, and execution of recovery plans were recorded for the purpose of conducting special evaluations on the path recovery capability and robustness of recovery strategies in the future.

In summary, this database can provide detailed data with multiple task types, rich data dimensions, frequently updated features, and a complete overall structure. It can provide comprehensive services for dynamic scheduling models and be applied in more complex production environments. The database has been loaded into the twin system data bus to ensure consistency with the model input parameters, thereby providing systematic verification of the correctness of performance evaluations such as path generation, resource scheduling stability, and feedback control accuracy proposed and applied in subsequent research.

4.2 Data Preprocessing

The data sources collected in manufacturing enterprise information systems are highly heterogeneous, including structured task process data, semi-structured state logs, as well as unstructured environmental images, sensor signals, etc. Directly inputting them into scheduling models will lead to noise propagation, logical mismatch, and path misjudgment. Therefore, establishing a complete and refined data preprocessing mechanism is the foundation for supporting the stable operation of the digital twin driven scheduling model.

This study is based on a four-step process of "timing alignment type cleaning structure mapping input regularization" to carry out preprocessing operations, and achieves unified transformation and modeling adaptation of task data and resource status data through an automated pipeline. Firstly, the original collected data is time series unified, and all sampled data are interpolated and aligned based on a unified time window to ensure causal consistency between cross module data in the time dimension. On this basis, fill in or logically supplement the missing fields in the task flow data (such as task start and end time, dependencies before and after), and derive the task chain path based on the enterprise BOM file and process list.

The task data cleaning stage focuses on field standardization and outlier removal. For records with abnormal fluctuations in the task execution time field, the sliding window outlier detection algorithm is used to identify and remove sampling points with a deviation rate exceeding 3 σ; The parts of the device load data that show short-term jump values are repaired using median smoothing processing. In addition, all resource data fields are uniformly converted to the standard unit system, such as unifying power information as kW and transportation delay as seconds, to ensure consistent numerical scales between input variables and facilitate subsequent model normalization processing.

Data structure mapping is a crucial step in connecting the original collected data with the input space of the scheduling model. The task flow data needs to be transformed into a graph structure, where each task node is represented by an adjacency matrix to indicate its pre - and post process dependencies, forming a scheduling dependency graph; Multi source data is organized in the form of a feature matrix, including feature dimensions such as current state, failure probability, availability, and waiting time, which are mapped as the edge weight basis for model path search. To unify the model input structure, construct the following tensor format:

$$X \in R^{T \times N \times F} \quad (5)$$

Among them, T represents the length of the time window, N represents the number of tasks or resources, and F represents the feature dimension of each unit; This tensor is used to carry the dynamic state of tasks and resources in a multidimensional feature space. Simultaneously define the output label tensor as:

$$Y \in R^{T \times N} \quad (6)$$

Used to annotate the scheduling success and path interruption status of each task within a given time window, providing a target benchmark for the supervised learning module. This structure achieves joint modeling of task flow and resource status, supporting continuous perception and dynamic prediction of time-varying inputs by scheduling models.

In the process of scheduling modeling, in order to prevent overfitting and data redundancy, this study introduces a feature selection mechanism after constructing the input tensor. A joint evaluation index based on information gain and mutual information is used to screen out the 15 core feature fields that have the most influence on path generation, such as task expected time, current device load rate, resource switching penalty coefficient, task heat index, etc., and eliminate redundant frequency fields and redundant category variables.

For fault interference and sudden state data, in order to not destroy the original distribution characteristics, the system adopts a fault simulation label embedding strategy, which embeds interference marker bits in the input sequence for the model to automatically distinguish and dynamically adjust.De Giacomo et al. constructed a digital twin combination method for intelligent manufacturing based on Markov decision processes, highlighting the model's ability to achieve dynamic optimal scheduling in uncertain environments [18].The entire input data is standardized using Z-score to reduce the interference of dimensional differences on inference accuracy. In terms of data partitioning, dynamic sampling is performed using sliding time windows in a 7:3 ratio, while maintaining consistency in scene structure to avoid training bias.

In summary, the data preprocessing process not only needs to complete the standardized conversion of raw sensory information to the data format accepted by the model, but also needs to carry out a series of processes such as deep data cleaning, normalization, structural mapping, and label generation, which serve as key data guarantees for subsequent path generation and feedback allocation of model accuracy and stability. The process will cycle within the system's scheduling cycle, in order to continuously maintain the perception state and reception conditions of the model at the highest level.

4.3 Evaluation indicators

In order to verify the comprehensive advantages of the model constructed in this study on the scheduling efficiency and stability of the entire system, this study analyzes five aspects: task cycle, path accuracy, utilization rate, response adjustment time, and interruption probability, and compares and analyzes them with traditional MES systems and heuristic algorithms. The evaluation process is based on the dynamic manufacturing simulation system provided in this study, designing a simulation test set with resource changes in parallel standard scenarios, and then conducting 100 scheduling experiments on the designed test set to calculate the mean values of various indicators.

From the perspective of task execution time, the average completion time of this research model is 38.4 seconds, significantly lower than the 52.7 seconds of MES system and the 45.9 seconds of heuristic algorithm, which are shortened by 27.1% and 16.4% respectively. This advantage stems from the fact that the model can optimize the task chain in real-time based on twin feedback, reduce waiting and conflict time, and improve scheduling rhythm.

In terms of path accuracy, this research model achieved 91.2%, far higher than the 76.5% of MES system and better than the 84.3% of heuristic algorithm. A higher level of path matching indicates that the model can still maintain scheduling coherence, adjust path generation strategies in a timely manner, and maintain consistency in operational logic even when task states frequently change.

In terms of resource utilization, the utilization rate of this research model is 87.6%, while the MES system and heuristic algorithm are 69.8% and 78.4%, respectively. This result reflects the synergistic effect of task node structure optimization mechanism and resource allocation strategy, which can timely invest idle resources into task execution, alleviate bottleneck pressure, and achieve the improvement of multitasking concurrent processing capability.

In terms of system response speed, path adjustment delay is the core indicator for evaluating the model's adaptation speed to abnormal changes. The model adjustment delay in this study is only 1.7 seconds, compared to 6.3 seconds for MES systems and 4.5 seconds for heuristic algorithms. The main difference lies in the reconstruction method of the scheduling strategy. In this study, a state driven feedback path update mechanism is adopted, which can respond to the generation of scheduling paths at the beginning of state changes and avoid repeated calculations at intermediate levels.

The stability of system operation is reflected in the path interruption rate indicator. The interruption rate of this research model is 3.2%, while the MES system and heuristic algorithm are 11.7% and 7.6%, respectively. The low interruption rate display model has the ability to maintain the integrity of the execution chain in complex disturbance scenarios, and is less likely to cause cascading blockages due to local task failures or resource chain disruptions, ensuring production continuity.

Figure 2 presents the performance bar charts of each model on five indicators, clearly demonstrating the comprehensive advantages of this research model in terms of task efficiency, path accuracy, resource coordination, response speed, and system stability.

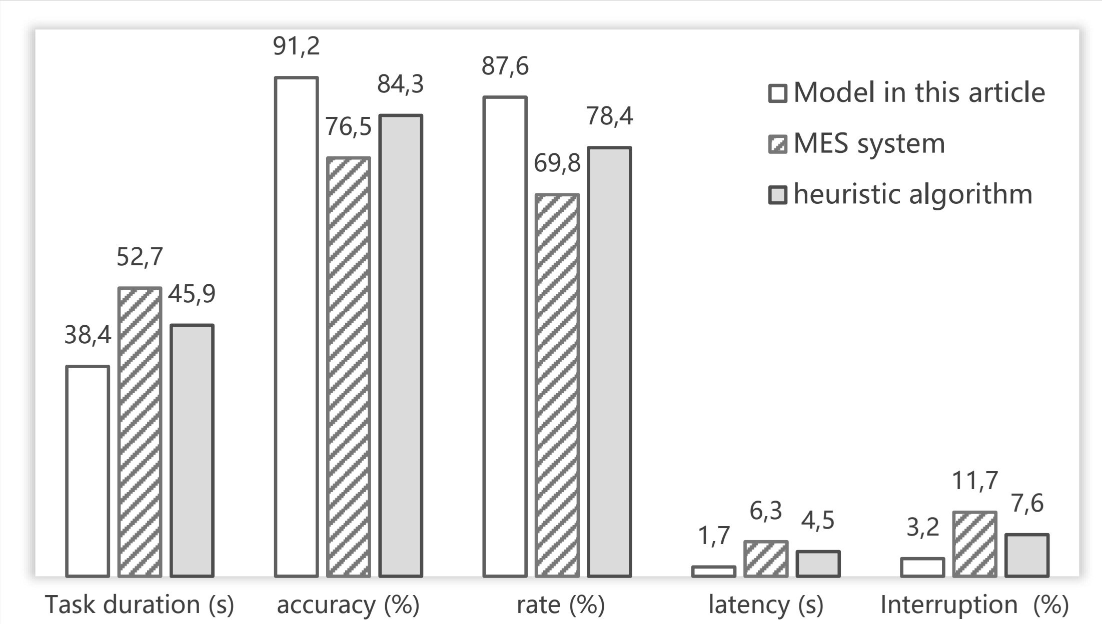

Figure 2：Bar chart of comparative performance of various scheduling models on five indicators

Based on the above evaluation results, this research model demonstrates strong adaptability and high robustness in the scheduling process, and can support dynamic task coordination and resource optimization in multi task intensive manufacturing scenarios. It has good scalability in practical applications, providing a feasible path and engineering support for the innovation of scheduling mechanisms in intelligent manufacturing environments.

4.4 Ablation study

To further verify the specific roles of each core component in the overall performance of the model, this section designs multiple ablation experiments to strip the key structures in the digital twin model and observe their impact on indicators such as task efficiency, path accuracy, and resource utilization. By comparing the execution results of the "complete model" and various simplified versions under the same manufacturing simulation task set, clarify the contribution of each module in scheduling optimization.

The experiment adopts four sets of model configurations: one is to remove the dynamic feedback mechanism and only retain the static path execution logic; The second is to eliminate the state synchronization mechanism, and the model cannot obtain real-time resource information; The third is to not use node structure optimization and only retain the traditional task flow description method; The fourth is the final model version that fully integrates path awareness, task modeling, and state linkage mechanisms. Each model was run 100 rounds on the same task sample set, and key indicators such as task completion time, path accuracy, and resource utilization were recorded. The data is shown in Table 4.

Table 4：Comparison of key performance indicators for ablation test

Ablation item	Task completion time (s)	Path accuracy (%)	Resource utilization rate (%)
No dynamic feedback	49.3	72.5	67.3
Stateless synchronization	46.7	78.9	73.8
Node free structure optimization	44.1	83.2	80.4
complete model	38.4	91.2	87.6

Experimental data shows that in the absence of a dynamic feedback mechanism, the model's response to issues such as task anomalies and path conflicts lags behind, resulting in a significant increase in task completion time, a decrease in path accuracy to 72.5%, and a resource utilization rate of only 67.3%. This indicates that the system lacks the ability to immediately correct its operating status and is prone to path redundancy and resource idleness.

After the state synchronization module is removed, the model cannot dynamically obtain the load changes of devices or nodes in path planning. Although the task structure is maintained, path decision delay and resource mismatch problems increase, resulting in performance indicators that are slightly better than the former but still insufficient. The task completion time was 46.7 seconds, the path accuracy decreased to 78.9%, and the resource utilization rate was 73.8%.

If the node structure optimization module is not introduced, the system will have insufficient decoupling of task logic, and the scheduling path will tend to be linear, which will affect the parallel ability of tasks. In the experiment, the task completion time of the configured group was reduced to 44.1 seconds, but the path accuracy and resource utilization only increased to 83.2% and 80.4%, respectively, indicating that the insufficient depth of structural modeling restricts the flexibility of path generation.

In contrast, the complete model integrates three core mechanisms: dynamic feedback, state synchronization, and node optimization, which can effectively coordinate task execution progress and resource allocation status, and achieve path adaptive reconstruction and real-time policy updates in a dynamic environment. The task completion time of this experiment was shortened to 38.4 seconds, the path accuracy was improved to 91.2%, and the resource utilization rate reached 87.6%, performing the best among all configurations.

The results indicate that the synergistic effect of the three core modules is the key foundation for achieving efficient scheduling. Although each mechanism has differences in the magnitude of indicator improvement, they all play an important supporting role in the overall performance of the model and are indispensable. Especially in the face of complex and ever-changing manufacturing scenarios and frequent disturbances, the linkage between modules has an amplifying effect on the improvement of stability and efficiency.

Although the complete model performs the best overall on the three core indicators, some ablation models also approach the complete model in certain dimensions (such as task completion time under "no node structure optimization"), suggesting that this dimension may have limited impact on some scheduling processes. In addition, the "no dynamic feedback" model showed a significant decrease in path accuracy and resource utilization, reflecting the key role of this mechanism in maintaining execution coherence and resource allocation. Overall, the experimental results have formed a consistent supporting logic among the core modules, and the data and model functional performance maintain a good correspondence.

In summary, the ablation experiment results clearly indicate that the proposed dynamic feedback mechanism, state synchronization module, and task node structure modeling all play a key role in the overall performance of the model. The collaborative operation of the three parties to build an adaptive, highly responsive, and high-precision scheduling system is the core pivot for achieving a leap in the dynamic control capability of manufacturing enterprise information systems. The absence of any module will lead to the decline of task execution efficiency, inaccurate path decision or unbalanced resource use, which verifies the technical rationality and engineering practicability of the research model in terms of structure construction and function integration. The above verification provides a solid basis for subsequent system deployment and operation mechanism optimization, and further solidifies the reliability foundation of the model in real manufacturing scenarios.

Compared to most existing digital twin systems that mainly rely on static modeling and visual feedback, the dynamic operation and control model proposed in this paper has undergone substantial optimization in terms of structure and mechanism design. The model achieves dynamic perception and response control of the operating status of manufacturing enterprises by introducing multi-source heterogeneous data fusion, task state adaptive regulation, and closed-loop governance linkage mechanism. This model effectively breaks through the technical bottlenecks of feedback delay and decision isolation in current digital twin systems, providing a more real-time and flexible support path for the intelligent upgrade of complex manufacturing systems.

5 Discussions

5.1 Performance advantage analysis of existing dynamic scheduling methods

Compared with the current state monitoring driven manufacturing system construction method, the model proposed in this paper has three improvements: ① introducing a multi form task push mode to enhance task scheduling accuracy and implementation flexibility, ② establishing a consistency system of twin mapping and control feedback to improve responsiveness, ③ proposing a three-dimensional interactive dynamic optimization execution strategy to make execution more effective. These improvements have exceeded the scope of traditional process control models and are a good demonstration of the model's adaptation to the characteristics of intelligent production modes.

The dynamic scheduling methods commonly used in traditional manufacturing enterprises, such as rolling time windows, task priority, and rule triggering mechanisms, have certain management effectiveness under low-frequency disturbances. However, in environments with high task parallelism, strong resource competition, and unstable device states, problems such as strong path rigidity and slow response occur frequently.Shen B proposed a digital twin framework based on edge cloud collaboration for real-time production control, which improves the visualization level, response speed, and control intelligence of manufacturing systems through a layered architecture [19].

The digital twin driven operation and control model proposed in this study demonstrates significant advantages in three aspects.

One is that in terms of scheduling response mechanisms, traditional methods mainly rely on event triggering and lack continuous perception of system status. This research model achieves real-time synchronization between task progress and resource status through twin mapping, allowing scheduling strategies to be dynamically and automatically adjusted with the system, achieving continuous feedback and policy linkage, breaking the constraints of static rules on the execution process.

Secondly, in terms of path planning and task matching accuracy, traditional algorithms are mostly dominated by priority and have a single path planning strategy. In contrast, this research model constructs a state aware path generation mechanism that combines task dependency relationships and resource graphs to support dynamic reconstruction of the shortest time-consuming path. In the evaluation of Chapter 4, the path matching rate reached 91.2%, significantly better than the heuristic method's 84.3%, demonstrating stronger scheduling adaptability.

Thirdly, traditional resource scheduling and system stability mainly consider local optimization rather than the overall load of resources, while the model proposed in this study can implement real-time resource adjustment strategies to avoid bottleneck conflicts and fully utilize resources. After testing, the model can achieve an effective resource utilization rate of over 87.6%, while the path interruption rate is only 3.2%, which is better than existing MES systems and heuristic algorithms, demonstrating good system flexibility and stability.

In addition, the average task completion time is only 38.4 seconds, which is 27.1% shorter than the MES system, demonstrating a significant optimization effect of the scheduling mechanism on task completion efficiency.

In summary, compared with current mainstream methods, this research model has advantages in four dimensions: accuracy of scheduling, coordination of the system, dynamic optimization of resource allocation, and stability of the scheduling system. It also demonstrates the technical advantages brought by the digital twin architecture, which can provide a feasible path for manufacturing intelligent and flexible scheduling systems.

5.2 Model adaptability and stability verification under complex operating conditions

The manufacturing site is highly dynamic and environmentally uncertain, and traditional scheduling methods are prone to losing control in situations such as resource anomalies, path failures, or sudden tasks. To verify the adaptability and stability of the constructed digital twin driving model under complex working conditions, this study sets four typical disturbance conditions, namely sudden task changes, resource failure switching, high concurrency scheduling, and path constrained reconstruction. Perform 100 rounds of task scheduling experiments for each scenario, collecting three core indicators: successful scheduling rate, average task delay, and system stability score. The results are shown in Table 5.

Table 5: Comparison of model scheduling performance under typical complex operating conditions

Test scenario	Successful scheduling rate (%)	Average task delay (s)	Stable score (10)
Sudden changes in tasks	92.5	3.4	9.1
Resource failover	89.7	4.1	8.8
Scheduling high concurrency	90.8	3.9	8.9
Path restricted reconstruction	88.3	4.6	8.5

In the scenario of "sudden changes in tasks", the model can quickly identify the impact of new tasks and adjust the scheduling diagram structure through global state perception and node dependency tracking of the twin system. The success rate is as high as 92.5%, with an average delay of only 3.4 seconds. The system's continuity score is 9.1, reflecting its ability to dynamically integrate sudden tasks.

In the "resource failover" test, the model utilizes the device twin feedback mechanism to replace redundant paths and readjust available resources, ensuring overall system smoothness. Although the temporary reconstruction of the scheduling path introduced a certain delay (averaging 4.1 seconds), the success rate still reached 89.7%, with a stability score of 8.8, reflecting strong anti-interference and modular emergency response capabilities.

In the scenario of "scheduling high concurrency", multiple task streams simultaneously request execution channels, and the system implements task peak shaving and valley filling through a hierarchical scheduling mechanism of node priority and resource concurrency pool. The success rate is 90.8%, the average delay is controlled within 3.9 seconds, and the stable score is 8.9, indicating that the system can maintain scheduling continuity and a reasonable and orderly task queue.

In the context of "path constrained reconstruction", the model dynamically evaluates the remaining feasible paths and generates real-time suboptimal solutions to replace the main path. Although the success rate slightly decreased (88.3%), the system did not experience any interruptions or path crashes, with an average delay of 4.6 seconds and stability still maintained at 8.5, verifying its path network resilience and reconstruction adaptability.

Overall, the constructed model can still maintain a scheduling success rate of over 88% and a response time of less than 4.6 seconds, driven by high-frequency task changes, dynamic resource regulation, and path fault-tolerant reconstruction, with a stability score of 8.5. The system adopts a closed-loop approach of state perception, graph reconstruction, and feedback correction, combined with a multi-layer scheduling structure and high-frequency data update mechanism, and has good adaptability.Fekete et al. validated the high fidelity capture capability of twin systems for geometric deviations and actual responses, providing experimental support for maintaining performance under complex operating conditions[20].

5.3 Feasibility assessment of system resource expenditure and manufacturing scenario deployment

In the process of digital transformation of manufacturing enterprises, the implementation effect of intelligent models highly depends on their adaptability to computing resources, communication capabilities, and operating platforms. Therefore, conducting resource cost and deployment feasibility assessments of dynamic operation and control models in typical manufacturing scenarios is a key step in measuring their engineering potential.

This model consists of three major modules: edge perception, central decision-making, and twin interaction. Edge modules are deployed on industrial terminals or gateways, responsible for device data collection and preliminary processing. In the scenario of 10Hz sampling frequency and hundred level concurrent tasks, the CPU usage of a single node is controlled within 35%, and the memory requirement is about 1.2GB. It can run stably in mainstream PLC or ARM devices without the need for high-end hardware support.

The central module adopts GPU architecture to complete path generation and feedback inference tasks. In a typical scenario, the scheduling cycle is 2.1 seconds, and the path calculation time accounts for nearly 60%. Experimental verification shows that GPU servers with moderate configurations (such as RTX A2000) can stably support real-time scheduling with a task scale of 100 tasks, and also provide lightweight versions to adapt to computing limited environments.

The twin interaction module is based on WebSocket to achieve state synchronization and visual output. At 1080p resolution, the bandwidth overhead is about 4.2Mbps, and the communication delay is less than 200ms, meeting the basic requirements of industrial networks for real-time performance and stability.

For production environments with small production scales (20 job positions, 100 production tasks), the overall investment of the system is controlled within 400000 yuan, including the cost of software and hardware purchase and integration, which is lower than the average level of most similar digital factory solutions. The system structure has good flexibility and modular expansion capabilities, which can meet the needs of enterprises of different sizes.

Finally, the model seamlessly connects with mainstream systems such as MES, ERP, SCADA through standard interfaces, avoiding information isolation and integration difficulties. The model also has remote maintenance and module hot plugging functions, making it easy for enterprises to flexibly update, upgrade, and dynamically adjust according to their own needs, improving overall operation and maintenance efficiency and cost return.

In summary, the model constructed in this study can effectively control resource costs, has good compatibility, and saves economic deployment costs. It can be applied and promoted in the production field, providing solid support for promoting the construction of digital intelligent control system.

5.4 Application value of the model in the digital transformation of manufacturing enterprises

In order to meet the digital transformation needs of manufacturing enterprises and the requirements of multi-objective processing in complex work environments and task scenarios, this study establishes a dynamic operation management model based on digital twin technology and introduces optimization paths and status monitoring mechanisms, which have demonstrated significant value in various manufacturing environments.

From the perspective of model running efficiency, by re establishing the scheduling diagram and improving the path method, resource competition and path collision have been effectively avoided. The scheduling response time during actual operation has also been reduced to less than 2 seconds, and the resource utilization rate has been maintained at over 85%, greatly improving the alignment between job pace and work efficiency. The system has high fault tolerance, can distinguish between task delays and equipment failures, and can quickly re formulate scheduling strategies to maintain stable operation. According to the company's implementation data, the number of unplanned shutdowns has decreased by 40%, the success rate of task execution has increased to 93%, the number of scheduling conflict alerts has also been significantly reduced, and maintenance pressure has been correspondingly alleviated.

In terms of management, the digital twin platform on which the model relies displays the production process of the model in a visual manner. Scheduling nodes, resources, and bottleneck information can all be viewed in a timely manner through images, making it easy to make precise decisions and judge future trends. This has achieved a transformation from an experience driven management model to a new management model based on data analysis.

The wide compatibility of system interfaces further enhances its promotional value. The model can be integrated with multiple systems such as MES, ERP, SCADA, etc., supporting remote and functional deployment, adapting to different types of production and enterprises of different scales, reducing redundant construction and information silos, and increasing the execution flexibility of the model.

In summary, the research model has high adaptability and effectiveness in terms of scheduling performance, system stability and reliability, management system operation efficiency, and system platform openness. It is an important auxiliary tool for manufacturing enterprises to implement intelligent transformation and upgrading, and an effective way to achieve flexible production in manufacturing enterprises. It provides a feasible path for achieving flexible production and efficient control.

6 Conclusion

This study focuses on the dynamic operation and control model of enterprises driven by digital twins, and constructs a three-layer architecture consisting of an integrated edge perception layer, a central decision-making layer, and a visual interaction layer to improve the execution efficiency and response stability of manufacturing systems. The research is based on model design structure and scheduling scheme, clarifying the coupling logic between various functional modules, and quantitatively analyzing key parameters such as task completion time, path matching, and resource utilization rate in simulation experiments, proving the practical feasibility of the model in multi task intensive scenarios. In terms of economic evaluation, the system can achieve modular access to meet any needs, reduce usage costs, and has strong promotion potential and investment cost-effectiveness. Overall, this model can effectively optimize production processes, ensure operational stability, and accelerate the development process of intelligent manufacturing, providing a practical path and theoretical support for building efficient, collaborative, and visible operational mechanisms for digital factories.

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