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SIMULATION-DRIVEN OPTIMIZATION FOR PRODUCTION PLANNING IN EQUIPMENT MANUFACTURING

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Abstract
Equipment manufacturing is characterized by multi-variety, small-batch production and frequent dynamic disturbances. Conventional production simulation is mainly used for offline validation and is rarely integrated with production planning, which limits its applicability in dynamic environments. This study develops a simulation-driven closed-loop rolling optimization framework based on a multi-agent discrete event simulation model. The framework integrates rolling horizon control, real-time interaction between simulation and optimization, and disturbance-triggered rescheduling. A coupling mechanism between the simulation clock and optimization process is established to support continuous plan adjustment. Simulation experiments in a real manufacturing workshop show that the proposed approach reduces order tardiness and makespan while maintaining stable equipment utilization under dynamic disturbances, compared with offline simulation-based optimization and conventional scheduling methods. The results indicate that production simulation can be integrated into planning decisions and used for dynamic adjustment in complex manufacturing environments.
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Key Words: Equipment Manufacturing, Production Planning Optimization, Multi-Agent Discrete Event Simulation, Simulation-Optimization Closed Loop, Rolling Horizon Optimization, Dynamic Production Scheduling

1. INTRODUCTION

Equipment manufacturing production systems are characterized by high structural complexity and pronounced multi-variety, small-batch production features [1, 2]. Under such conditions, dynamic disturbances – such as equipment failures, urgent order insertions, and material delivery delays – are frequently encountered, rendering traditional static production plans difficult to sustain [3]. Production simulation has long been recognized as a core tool for analysing and optimizing manufacturing systems [4-7]. However, its current application remains predominantly confined to offline modelling and ex post validation, and its potential for production planning optimization has not been fully exploited. Existing research in production simulation has largely focused on improving model fidelity [8, 9], while the development of integrated approaches that tightly couple simulation with production planning optimization remains limited. In particular, a lack of technical frameworks enabling real-time interaction between simulation and optimization, as well as simulation-driven dynamic adjustment of production plans, has constrained the applicability of simulation in highly dynamic equipment manufacturing environments. The present study is of both theoretical and practical significance. From a theoretical perspective, the framework contributes to the advancement of dynamic closed-loop production simulation theory and enriches research on the integration of simulation and production planning optimization. From an engineering perspective, a deployable simulation-driven production planning optimization approach is provided for equipment manufacturing enterprises, facilitating improved responsiveness to dynamic disturbances and enhanced production efficiency.

In related research, discrete event simulation and multi-agent simulation have become the dominant paradigms for workshop-level production modelling [10-13]. With respect to the integration of simulation and production optimization, most existing studies have adopted offline approaches [14, 15], in which real-time feedback and dynamic adjustment mechanisms are absent. A limited number of semi-closed-loop studies have been reported; however, rolling horizon optimization and disturbance-adaptive mechanisms have not been fully implemented [16, 17], and thus the capability to address stochastic production disturbances remains insufficient. The central research gap can therefore be identified as the absence of a simulation-centred production planning optimization framework that operates in a real-time closed loop with optimization algorithms and supports adaptive updates based on rolling horizon. As a result, current approaches remain inadequate for addressing the dynamic production characteristics inherent in equipment manufacturing systems.

To address the identified research gap, a systematic investigation was conducted with the core components below. First, a multi-agent simulation foundation for equipment manufacturing production systems is constructed to enable high-fidelity representation of production processes. Second, a simulation-optimization closed-loop rolling adaptive optimization framework is designed, which constitutes the sole core innovation of this study. Finally, the effectiveness of the proposed approach is validated through simulation experiments. The overall technical route follows a structured progression, including data acquisition, simulation modelling, closed-loop framework construction, simulation experimentation, and result analysis, thereby ensuring methodological rigor and practical feasibility. The primary contribution lies in the development of a production simulation-optimization closed-loop rolling adaptive optimization framework based on a discrete event simulation clock. Within this framework, the multi-agent simulation environment serves as a dynamic system carrier. Through the coupling of a fixed rolling horizon with simulation progression, real-time feedback of simulation states, disturbance-triggered online simulation calibration, and the feedback execution of optimization decisions, an integrated and dynamically iterative mechanism between simulation and production planning is achieved. As a result, the limitations of the traditional offline simulation paradigm are effectively overcome.

The remainder of this study is organized below. Section 2 presents the construction of the multi-agent simulation foundation. Section 3 details the design of the closed-loop rolling adaptive optimization framework. Section 4 evaluates the performance of the proposed method through simulation experiments. Finally, Section 5 summarizes the main findings and key contributions.

2. MULTI-AGENT SIMULATION MODELLING FRAMEWORK

In this section, a multi-agent simulation foundation for the equipment manufacturing production system is constructed to provide a high-fidelity experimental environment for the subsequent closed-loop optimization framework. The equipment manufacturing workshop is abstracted as a discrete event dynamic system, within which the simulation boundary is defined by core production elements, including machines, operations, materials, orders, and logistics processes. A multi-agent simulation paradigm is adopted to establish the model structure. Four categories of core agents – order agents, machine agents, material agents, and transport agents – are defined to represent the primary functional entities of the production process. System evolution is driven by a discrete event simulation clock, in which key events, including operation completion, machine failure, material arrival, and urgent order insertion, are used to trigger state transitions. To accurately capture the dynamic characteristics of the production system, real-world manufacturing data are incorporated. The time between machine failures is modelled using a Weibull distribution, while operation processing times are assumed to follow a normal distribution.

The input to the simulation model consists of essential enterprise production data, including the bill of materials, process routes, machine parameters, and order information. The model outputs a multidimensional dataset comprising global system states, machine utilization, order progress, and disturbance event records. These outputs are directly utilized as the core input source for the simulation-optimization closed-loop rolling framework, thereby ensuring seamless integration between the simulation foundation and the proposed optimization mechanism. Consequently, reliable dynamic environmental support is provided for the adaptive optimization of production planning. The physical and logical architecture of the multi-agent production simulation model for equipment manufacturing is illustrated in Fig. 1.

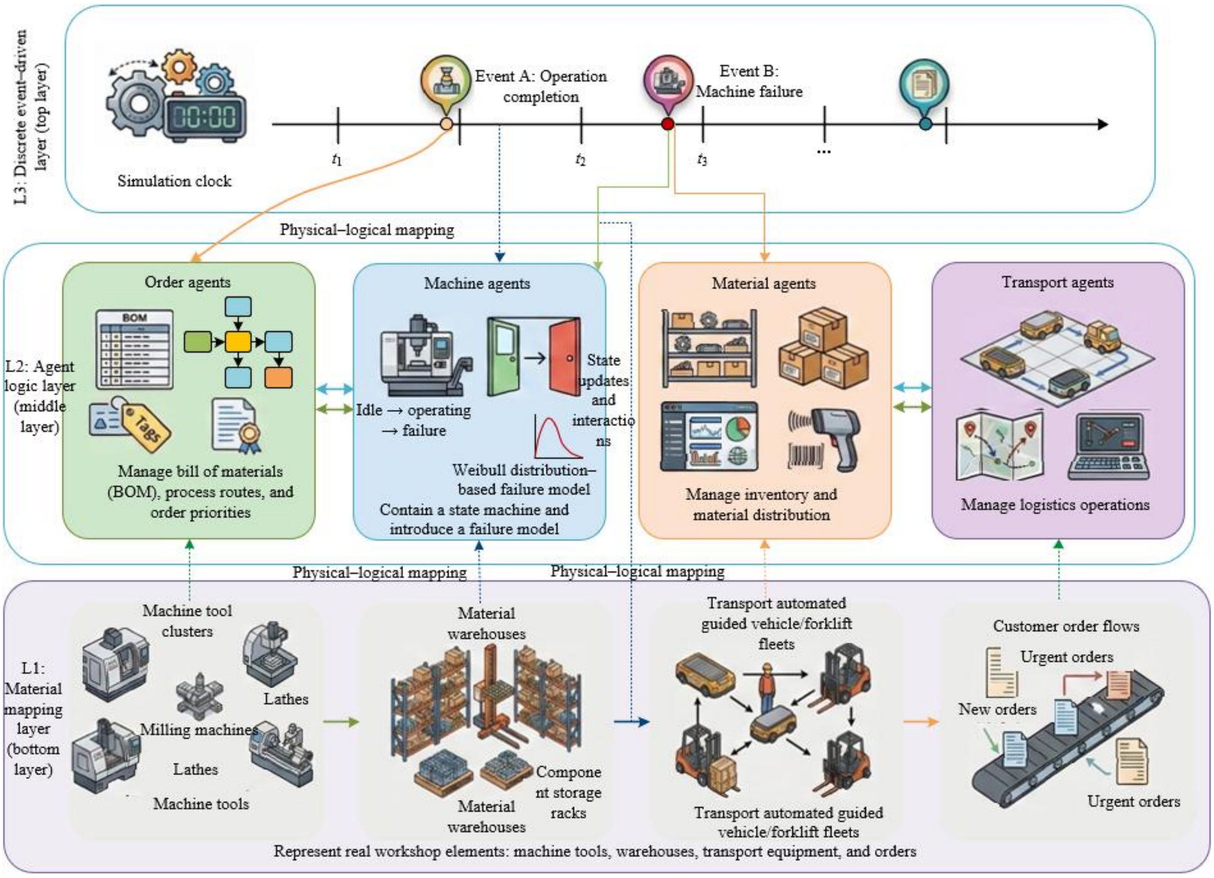

Figure 1: Physical and logical architecture of the multi-agent production simulation model for equipment manufacturing.

3. CLOSED-LOOP ROLLING OPTIMIZATION FRAMEWORK

3.1 Overall framework design

The proposed simulation-optimization closed-loop rolling adaptive optimization framework is constructed with production simulation as its core, forming an integrated closed-loop operational system. The overall architecture consists of four key components: the multi-agent simulation execution module, the rolling time horizon control module, the optimization decision module, and the data interaction module. Within this framework, the conventional limitation of production simulation as a tool restricted to solution validation is overcome. The simulation model is instead defined as a dynamic digital representation of the real production system, in which optimization decisions are generated entirely based on the system states obtained from simulation outputs. These decisions are subsequently fed back into the simulation environment through real-time data interaction, thereby driving continuous system evolution. Through this mechanism, a tightly coupled and dynamically interactive closed-loop operation is established, in which simulation-based system evolution and optimization-driven decision-making are iteratively integrated and synchronized in real time. Fig. 2 illustrates the simulation-optimization closed-loop rolling operational mechanism based on a discrete event clock.

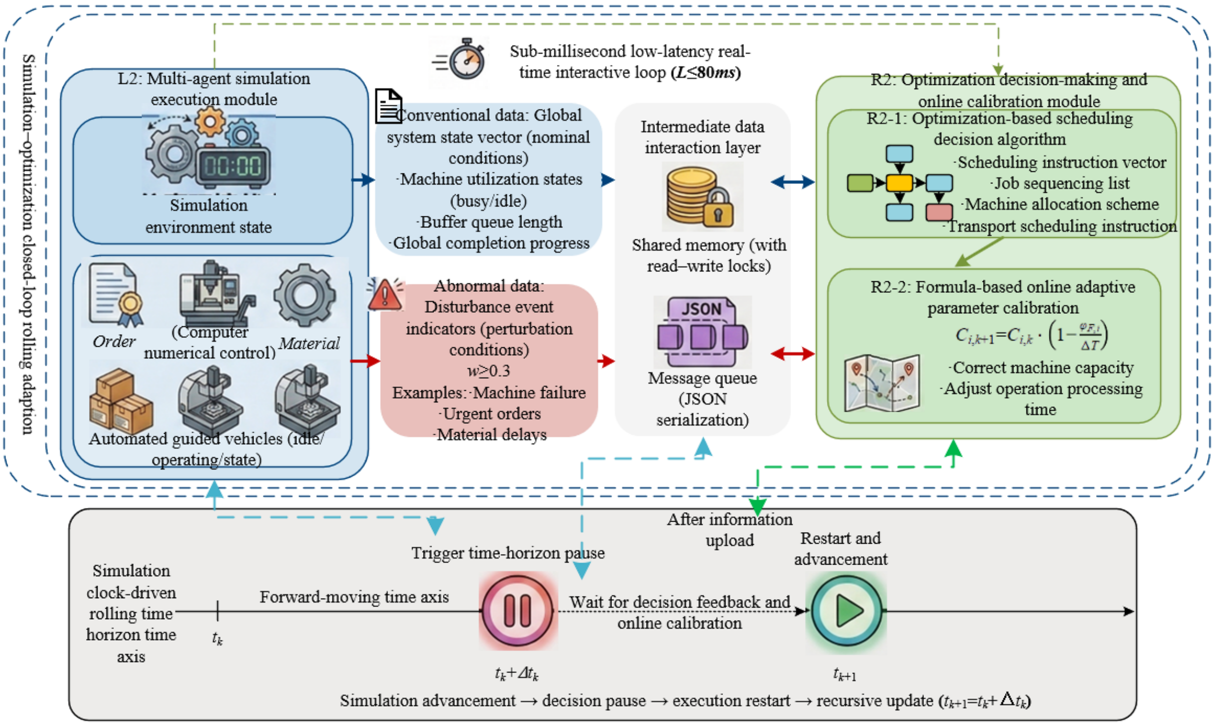

Figure 2: Simulation-optimization closed-loop rolling operational mechanism based on a discrete event clock.

3.2 Key technical details

- Coupling mechanism between the simulation clock and rolling time horizon

In this mechanism, the discrete event simulation clock is adopted as the fundamental temporal reference, and a dual-driven coupling architecture is constructed by integrating a fixed rolling step size, thereby ensuring strict temporal synchronization between simulation and optimization processes. The discrete event simulation clock operates based on an event priority queue to manage production progression. Disturbance events, such as machine failures and urgent order insertions, are assigned the highest priority, whereas routine events, including operation completion and material arrivals, are assigned secondary priority. This priority structure ensures that critical events are processed with precedence.

The step size of the rolling time horizon is initially set to 1 h and is adaptively adjusted according to production dynamics. Specifically, when the fluctuation in average machine utilization over three consecutive rolling time horizons is less than 5 %, the step size is reduced, whereas it is increased when the fluctuation exceeds 15 %. The global simulation clock is updated recursively according to $t_{k+1} = t_k + \Delta T_k$, where t_k denotes the starting time of the k^{th} rolling time horizon, and ΔT_k represents the adaptively adjusted step size. When the simulation advances to $t_k + \Delta T_k$, a time horizon trigger is activated, and a time-horizon pause is executed. During this pause, all event scheduling processes are temporarily frozen, and a global system state vector is generated, including machine idle/busy states, buffer queue lengths, remaining order due times, and global production completion progress. Subsequently, the optimization decision module computes and outputs a scheduling decision vector. After these decisions are loaded into the simulation module, the simulation is resumed and continues to advance to t_{k+1}. Through the iterative closed-loop process of time-horizon pause → decision execution → restart advancement, the synchronization error between the simulation and optimization processes is controlled within $\varepsilon \leq 0.01$ h, thereby fundamentally resolving the temporal misalignment issue inherent in conventional decoupled simulation and optimization approaches.

- Low-latency real-time closed-loop interaction between simulation and optimization

A hybrid interaction architecture combining shared memory and a message queue is established to enable sub-100-millisecond data exchange between the simulation platform and the optimization algorithm. The interaction latency is strictly controlled within $L \leq 80$ ms. Within this architecture, the shared memory module is partitioned into independent memory blocks to store the global system state, scheduling instructions, disturbance events, and calibration parameters. Read-write locking mechanisms and data validation flags are implemented to prevent concurrent read-write conflicts. The message queue module operates under a first-in, first-out protocol, in which message bodies are serialized in JSON format. Message headers are defined to include message type, timestamp, and data length, thereby ensuring ordered and complete data transmission.

The data flow follows a seamless closed-loop logic of state perception → decision generation → instruction execution. The simulation module writes the global system state vector and disturbance markers into shared memory and triggers an update signal. Upon subscribing to this signal via the message queue, the optimization algorithm retrieves the relevant data and generates three categories of scheduling instructions: job sequencing, machine assignment, and transport scheduling. After data validation, these instructions are written into the instruction block of shared memory, and an execution signal is issued. The simulation module, upon detecting this signal, executes the received instructions and updates the system state accordingly, thereby completing a full closed-loop interaction cycle. To ensure interaction reliability, dual mechanisms of packet retransmission and data validation are introduced. The message queue is configured with a maximum of three retransmission attempts, beyond which a fallback scheduling strategy is triggered. Data stored in shared memory are verified using a Cyclic Redundancy Check 32 (CRC32) checksum to ensure integrity. Through these mechanisms, stable closed-loop interaction and high data accuracy are effectively guaranteed.

- Disturbance identification and online calibration based on simulation outputs

In this stage, dynamic consistency between the simulation model and the real production system is achieved through disturbance intensity quantification and online adaptive parameter calibration. First, disturbance intensity metrics are defined for three categories of disturbances: machine failures, urgent order insertions, and material delivery delays. The overall disturbance intensity is calculated as a weighted sum of the three components, expressed as $\varphi = \omega_F\varphi_F + \omega_O\varphi_O + \omega_M\varphi_M$, where ω_F, ω_O, and ω_M denote the weighting coefficients satisfying $\omega_F + \omega_O + \omega_M = 1$. A global threshold $\varphi_O = 0.3$ is defined, and when the overall disturbance intensity exceeds this threshold, the online calibration procedure is triggered. The calibration process is executed without interrupting or restarting the simulation. Instead, a parameter iterative correction approach is adopted to update key system parameters in real time. The machine capacity is updated according to the following equation:

$$C_{i,k+1} = C_{i,k} \cdot \left(1 - \frac{\varphi_{F,i}}{\Delta T}\right) \tag{1}$$

Operation processing times are updated using a sliding average method, given by $T_{l,k+1} = \alpha T_{l,k} + (1\text{-}\alpha)\hat{T}_{l,k}$, where α is the smoothing coefficient. After calibration, model consistency is verified to ensure that deviations remain within acceptable bounds. The validation metric is defined as the relative deviation:

$$\delta = \frac{\hat{X} - X_{act}}{X_{act}} \times 100\ \% \tag{2}$$

where, $\hat{X}$ denotes the simulation output metric, and X_{act} represents the corresponding real production metric. Calibration is considered valid when $\delta \leq 5\ \%$. If this condition is not satisfied, parameter adjustment and iterative calibration are repeated until convergence is achieved. Through this mechanism, high consistency between the simulation model and the real production system is maintained, thereby providing a reliable dynamic simulation environment for optimization decision-making.

4. EXPERIMENTAL VALIDATION AND ANALYSIS

4.1 Simulation experimental environment

The simulation experiments were conducted using the AnyLogic platform, which is widely recognized as a leading tool in the field of production simulation. The platform provides robust support for multi-agent modelling and discrete event simulation, enabling accurate representation of the dynamic characteristics of equipment manufacturing production systems. A component processing workshop from a large-scale equipment manufacturing enterprise was selected as the case study. The workshop consisted of 20 processing machines and produced five categories of core products, each involving 12 key operations. This configuration is representative of a typical multi-variety, small-batch production environment. All input data used in the simulation were derived from three consecutive months of real production records from the enterprise. These data included the bill of materials, process routes, machine parameters, order information, machine failure records, and material supply data. The use of real-world production data ensures the authenticity and representativeness of the experimental scenarios, thereby providing a reliable foundation for the credibility of the experimental results.

4.2 Simulation model validation

To ensure that the simulation model can serve as a valid surrogate for the real production system, a dual validation approach combining *t*-tests and relative error analysis was employed to assess model fidelity. Three key performance indicators – monthly production output, average machine utilization, and order tardiness rate – were selected for comparative validation. The experimental results are presented in Table I.

Table I: Comparison of simulation model outputs and real production system metrics with fidelity validation.

Validation metric	Real production value	Simulation output value	Relative error (%)	*t*-statistic	*p*-value	Validation result
Monthly production (units)	1286.3	1268.7	1.37	1.82	0.11	No significant difference
Average machine utilization (%)	78.5	76.2	2.93	1.67	0.14	No significant difference
Order tardiness rate (%)	8.2	7.9	3.66	1.75	0.12	No significant difference

As shown in Table I, the relative errors between simulation outputs and real production values are all below 5 %. Furthermore, the *t*-test results indicate that all *p*-values exceed 0.05, suggesting that no statistically significant differences exist between the simulation model and the real production system. These findings demonstrate that the simulation model exhibits a high level of fidelity and satisfies the requirements for experimental validation. Consequently, the model can be regarded as a reliable surrogate for the real production system, providing a credible foundation for subsequent optimization experiments and ensuring the validity of the obtained results.

4.3 Comparative experimental design

To evaluate the effectiveness of the proposed simulation-optimization closed-loop rolling adaptive optimization framework, three groups of comparative experiments were designed around the single core innovation, with clearly defined grouping logic and evaluation metrics to ensure methodological rigor and experimental relevance. Control Group 1 adopted the conventional offline simulation-based optimization approach. In this setting, a simulation model was first constructed, followed by a single simulation analysis, after which a fixed production plan was generated. No real-time feedback or dynamic adjustment mechanism was incorporated. Control Group 2 employed classical scheduling rules, including first-come, first-served, earliest due date, and shortest processing time, combined with open-loop simulation. In this configuration, simulation was used solely to evaluate scheduling performance, and no closed-loop optimization mechanism was implemented. Experimental Group utilized the proposed closed-loop rolling simulation optimization framework, achieving real-time interaction between simulation and optimization and dynamic iterations.

Six key performance indicators were selected for evaluation: on-time delivery rate, average machine utilization, average completion time, maximum completion time, order tardiness rate, and disturbance-adaptive robustness. The disturbance-adaptive robustness was quantified by the degradation rate of key performance indicators under disturbance scenarios. Each experimental group was independently executed 30 times, and the mean and standard deviation were calculated as the final results. This design ensures the statistical reliability of the experimental findings.

4.4 Simulation experimental results and analysis

- Quantitative results analysis

The quantitative statistical results of the three experimental groups are presented in Table II, providing a direct comparison of the optimization performance across different methods.

Table II: Quantitative statistical results of the three experimental groups (mean ± standard deviation).

Evaluation metric	**Control Group 1** (Offline simulation optimization)	**Control Group 2** (Classical scheduling + Open-loop simulation)	**Experimental Group** (Closed-loop rolling optimization framework)
On-time delivery rate (%)	79.3 ± 2.8	72.6 ± 3.5	92.8 ± 1.7
Average machine utilization (%)	75.8 ± 2.1	70.4 ± 2.7	84.5 ± 1.5
Average completion time (h)	148.6 ± 5.3	162.4 ± 6.1	127.3 ± 4.2
Makespan (h)	189.2 ± 7.8	203.5 ± 8.4	156.7 ± 6.3
Order tardiness rate (%)	9.7 ± 1.6	14.2 ± 2.3	3.2 ± 0.9
Disturbance-adaptive robustness (%)	18.5 ± 2.4	25.3 ± 3.1	7.8 ± 1.2

As shown in Table II, all evaluation metrics of the experimental group exhibit significant improvements compared with both control groups, thereby demonstrating the core advantages of the proposed closed-loop rolling optimization framework. Compared with Control Group 1, the experimental group achieves an increase of 13.5 percentage points in on-time delivery rate and 8.7 percentage points in average machine utilization. Meanwhile, the average completion time is reduced by 21.3 h, the order tardiness rate is decreased by 6.5 percentage points, and disturbance-adaptive robustness is improved by 10.7 percentage points. In comparison with Control Group 2, the improvements are even more pronounced. Specifically, the on-time delivery rate is increased by 20.2 percentage points, the order tardiness rate is reduced by 11.0 percentage points, and disturbance-adaptive robustness is enhanced by 17.5 percentage points. From the perspective of variability, the standard deviations of all evaluation metrics in the experimental group are consistently lower than those of both control groups. This indicates that the proposed method exhibits greater stability and is less sensitive to stochastic disturbances, further confirming the effectiveness of the closed-loop rolling mechanism.

- Dynamic disturbance simulation analysis

To evaluate the adaptability of the proposed method under dynamic disturbance conditions, two representative disturbance scenarios were designed: machine failure (with a 20 % increase in failure rate) and urgent order insertion (with the proportion of urgent orders increased to 30 %). The performance degradation of the three methods under these disturbance scenarios was compared, and the results are presented in Table III.

Table III: Comparison of performance degradation rates under dynamic disturbance scenarios (%).

Disturbance scenario	Evaluation metric	Control Group 1	Control Group 2	Experimental Group
Machine failure	On-time delivery rate degradation	12.3	18.7	4.5
	Average machine utilization degradation	8.9	13.2	2.7
	Increase in order tardiness rate	15.6	22.4	5.8
Urgent orders	On-time delivery rate degradation	10.7	16.3	3.9
	Average machine utilization degradation	7.5	11.8	2.2
	Increase in order tardiness rate	13.4	19.6	4.9

As shown in Table III, performance degradation is observed across all methods under both disturbance scenarios; however, the degradation rates of the experimental group are significantly lower than those of the two control groups. Under the machine failure scenario, the degradation in on-time delivery rate for the experimental group is limited to 4.5 %, which is substantially lower than that of Control Group 1 (12.3 %) and Control Group 2 (18.7 %). Similarly, the increase in order tardiness rate is 5.8 %, compared with 15.6 % and 22.4 % for the two control groups, respectively. Under the urgent order scenario, the experimental group again exhibits the smallest performance degradation across all evaluation metrics. In particular, the reduction in average machine utilization is only 2.2 %, highlighting the strong adaptive capability of the proposed closed-loop rolling optimization framework. This superior performance can be attributed to the integration of disturbance identification and online calibration mechanisms within the framework, through which disturbances are detected in real time and optimization strategies are dynamically adjusted. In contrast, Control Group 1 relies on an offline optimization approach that lacks responsiveness to disturbances, while Control Group 2 employs an open-loop simulation strategy without dynamic adjustment capability, resulting in substantial performance degradation.

- Simulation sensitivity analysis

To quantify the effects of the rolling step size and disturbance intensity on optimization performance and to provide practical guidance for parameter configuration in real production environments, a simulation-based sensitivity analysis was conducted. The rolling step size (0.5 h, 1 h, 1.5 h, and 2 h) and disturbance intensity (10 %, 20 %, 30 %, and 40 %) were selected as experimental variables. Three key performance indicators – on-time delivery rate, average machine utilization, and average completion time – were adopted as evaluation metrics. The corresponding experimental results are presented in Fig. 3.

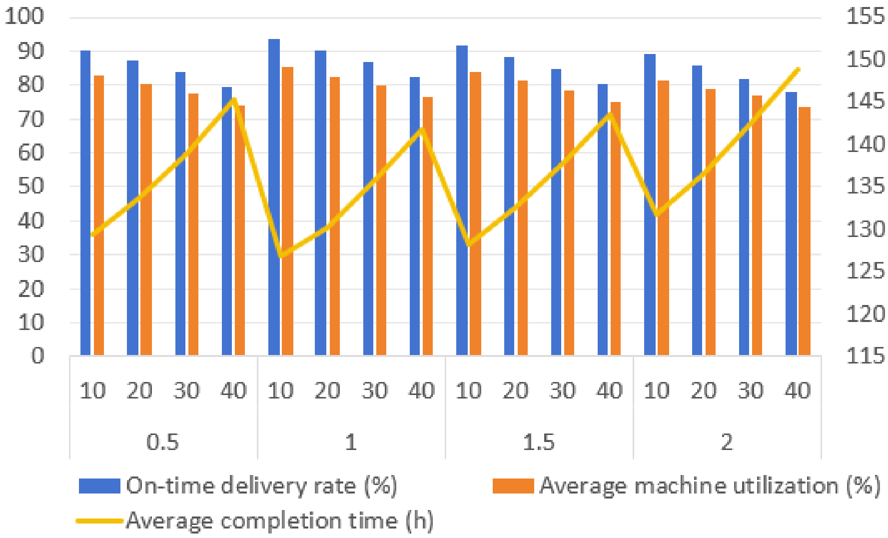

Figure 3: Results of the simulation sensitivity analysis.

The sensitivity analysis results presented in Fig. 3 indicate that both the rolling step size and disturbance intensity exert significant effects on optimization performance. When the rolling step size is set to 1.0 h, all evaluation metrics achieve optimal performance. If the step size is excessively small (0.5 h), the frequency of interaction between simulation and optimization is increased, resulting in higher computational cost and reduced optimization efficiency. Conversely, when the step size is excessively large (1.5 h or 2.0 h), the responsiveness of the optimization process is diminished, preventing timely adaptation to dynamic disturbances and leading to performance degradation. As disturbance intensity increases, all optimization performance indicators deteriorate. When the disturbance intensity is less than or equal to 20 %, the on-time delivery rate remains above 88 %, and the average machine utilization exceeds 80 %, indicating satisfactory optimization performance. However, when the disturbance intensity exceeds 30 %, a pronounced decline in performance is observed. Under such conditions, it becomes necessary to adjust the rolling step size and disturbance weighting coefficients to enhance the robustness of the framework. From a practical implementation perspective, it is recommended that the rolling step size be configured at 1.0 h. When the disturbance intensity is less than or equal to 20 %, default parameter settings can be maintained. When the disturbance intensity exceeds 20 %, the rolling step size should be reduced to 0.5 h, and the weighting coefficient associated with machine failure disturbances should be increased to achieve improved optimization performance. These parameter configuration guidelines provide actionable support for real-world deployment in production environments.

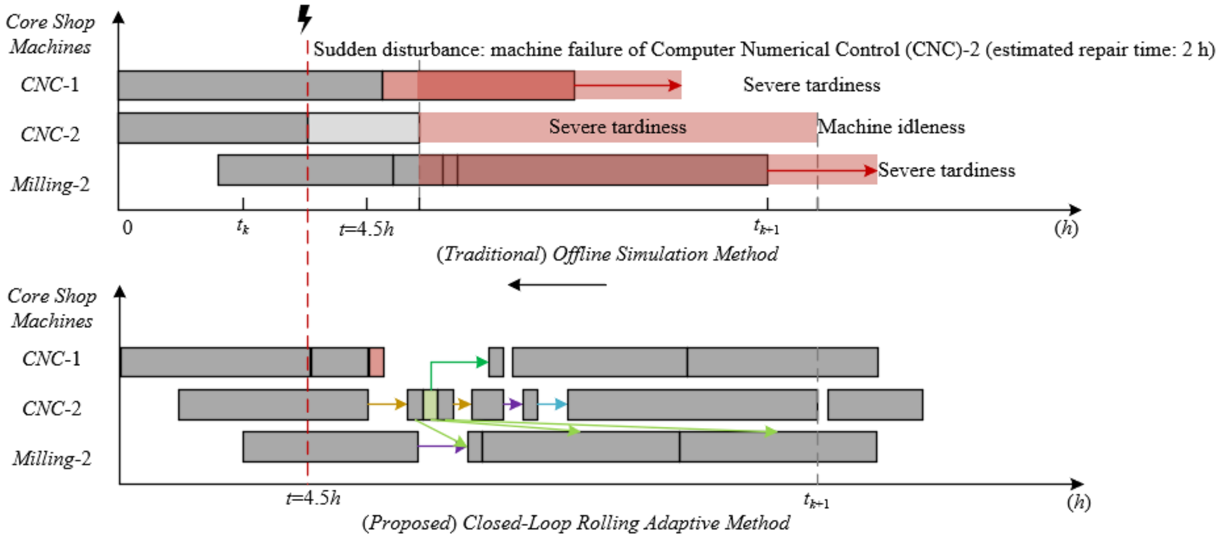

Figure 4: Comparison of dynamic scheduling processes (Gantt chart representation).

To further validate the superiority of the proposed closed-loop rolling adaptive optimization framework in handling discrete dynamic disturbances, a comparative experiment on dynamic scheduling processes was conducted based on high-fidelity system simulation. As illustrated in Fig. 4, when a machine failure disturbance is introduced to Computer Numerical Control-2 (CNC-2) at $t = 4.5$ h, the traditional offline simulation scheduling approach exhibits substantial limitations. Due to the absence of real-time state feedback and dynamic adjustment mechanisms, the affected operations and their subsequent tasks experience severe cascading delays across the entire workshop. Consequently, the final completion time significantly exceeds the expected step size. In contrast, within the proposed closed-loop rolling adaptive optimization framework, the disturbance is immediately detected, and a rescheduling mechanism is promptly triggered. Through optimization-driven decision-making, tasks originally assigned to the failed machine are rapidly reallocated to alternative machines, such as CNC-1 and Milling-1. As a result, the overall completion time of the system is effectively reduced, and machine idleness is significantly mitigated.

Overall, the experimental results demonstrate that the proposed simulation-optimization closed-loop rolling adaptive optimization framework achieves superior performance under both static and dynamic disturbance scenarios. Compared with conventional offline simulation-based optimization and classical scheduling methods, substantial improvements are observed in production efficiency and order delivery capability. These findings indicate that the framework provides a viable engineering solution for transforming production simulation from a static validation tool into a dynamic optimization engine.

5. CONCLUSION

To address the challenges posed by dynamic disturbances in multi-variety, small-batch production environments of equipment manufacturing enterprises, a simulation-centred approach was adopted. A multi-agent simulation foundation for the equipment manufacturing production system was constructed to accurately represent the dynamic characteristics and interactions within the production process. On this basis, a simulation-optimization closed-loop rolling adaptive optimization framework was proposed, enabling simulation-driven real-time optimization of production planning. Through this framework, the fundamental limitations of traditional offline simulation – namely, its disconnection from production planning optimization and its inability to adapt to dynamic production environments – were effectively overcome. The academic contributions to the field of production simulation can be summarized in two main aspects. First, the theoretical and methodological foundation of dynamic closed-loop production simulation has been advanced, overcoming the conventional paradigm in which production simulation is confined to offline validation and establishing a framework for real-time interaction between simulation and optimization. Second, a reusable engineering paradigm for simulation-driven production optimization has been developed, providing a standardized approach and technical support for the deep integration of production simulation into equipment manufacturing production planning optimization.

The proposed simulation-optimization closed-loop rolling adaptive optimization framework demonstrates strong generality and practical applicability, and can be extended to various discrete manufacturing workshops. It provides a feasible and effective technical solution for equipment manufacturing enterprises to respond to dynamic disturbances, enhance production efficiency, and improve order delivery performance. Future work can be directed toward deeper integration of the proposed framework with digital twin technology to further enhance the fidelity and real-time capabilities of closed-loop simulation. Such integration is expected to facilitate the transition of production simulation from a traditional analytical tool to a central optimization engine, thereby providing stronger support for the intelligent transformation of advanced equipment manufacturing systems.

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