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ROBUST SCHEDULING UNDER DISRUPTIONS USING TRANSFORMERS AND MONTE CARLO SIMULATION

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Abstract
Dynamic job shop scheduling is often affected by uncertainties such as machine failures and process delays. Traditional robust scheduling methods have limitations including high computational complexity, insufficient adaptability, and limited accuracy in risk assessment. To address these problems, this paper proposes an adaptive robust scheduling framework that integrates the sequence modelling capability of Transformers and the risk assessment advantages of Monte Carlo (MC) simulation. The core innovation of this framework is the design of a Transformer-driven disturbance–performance mapping mechanism and an MC-enhanced robustness evaluation module, enabling deep coordination between scheduling decisions and disturbance risk assessment. Comparative experiments based on a Python/SimPy discrete-event simulation platform verify that the proposed method exhibits significant advantages in makespan, tardiness rate, and robustness index, while improving the efficiency of robustness evaluation. This study provides an efficient paradigm for robust scheduling under production uncertainty scenarios.
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Key Words: Robust Scheduling, Uncertainty Disruptions, Transformer Model, Monte Carlo (MC) Simulation, Production Simulation, Dynamic Job Shop Scheduling

1. INTRODUCTION

Dynamic job shop scheduling is a core component of intelligent manufacturing systems [1, 2], and its optimization level directly determines production efficiency, cost control, and order delivery capability [3]. During the production process, random disruptions such as machine failures, dynamic order changes, and fluctuations in processing times are widespread [4, 5]. These disruptions easily undermine the feasibility of predefined scheduling plans, leading to a series of chain problems including production delays, resource waste, and cost increases [6]. Therefore, the core requirement of robust scheduling lies in simultaneously considering scheduling efficiency and adaptive response capability to unexpected disruptions, so as to maintain the stable operation of production systems under uncertain environments [7, 8].

Traditional robust scheduling methods, such as static robust scheduling and stochastic programming, suffer from significant technical bottlenecks. Their computational complexity grows exponentially with the number of disruption scenarios, making it difficult to meet the decision-making requirements of real-time production [9-11]. Existing deep learning-based scheduling methods, represented by deep reinforcement learning, possess a certain degree of adaptive control capability [12], but lack systematic assessment of disruption risks, making it difficult to balance efficiency and robustness. Although MC simulation has been widely applied in scheduling risk assessment [13, 14], it is mostly executed independently of decision models and has not been deeply integrated with advanced sequence modelling techniques. As a result, robustness evaluation efficiency and scheduling decision accuracy are difficult to achieve simultaneously, and such approaches fail to adapt to complex dynamic disruption scenarios [15-18].

This paper proposes an adaptive robust scheduling framework that integrates Transformers and MC simulation, with the core objective of achieving fast, high-precision, and adaptive robust scheduling decisions, and addressing the contradiction between efficiency and accuracy caused by the separation of decision-making and risk assessment. The key innovation of this framework lies in empowering the MC simulation-based risk assessment process through Transformers, constructing an integrated mechanism of scheduling decision-making and robustness verification. By leveraging the advantages of sequence modelling, the framework strengthens the representation of the relationship between disruptions and scheduling performance, while using MC simulation as the core support to realize accurate validation and optimisation of innovative scheduling solutions.

The remainder of this paper is organized as follows. Section 2 reviews related research on robust scheduling, Transformer applications, and MC simulation, and clarifies existing research gaps and the contributions of this study. Section 3 elaborates the technical details of the proposed framework, including problem formulation, core module design, and the collaborative optimisation process. Section 4 conducts comparative experiments based on a discrete-event simulation platform to verify the effectiveness and superiority of the proposed method. Section 5 summarizes the research conclusions, analyses challenges for industrial deployment, and discusses future research directions. This paper focuses on methodological innovation and simulation-based validation, providing technical support for robust scheduling under production uncertainty scenarios.

2. METHOD

2.1 Problem formalization

This study investigates the dynamic job shop robust scheduling problem. The scheduling object consists of processing tasks of n jobs on m machines. Each job contains multiple operations, and the operations must satisfy machine assignment constraints and precedence constraints. The job set is defined as $J = \{J_1, J_2, \ldots, J_n\}$, and the machine set is defined as $M = \{M_1, M_2, \ldots, M_m\}$. O_{ij} denotes the j^{th} operation of job J_i, and T_{ij} represents the processing time of operation O_{ij}. Considering uncertainties in the production process, this study focuses on modelling two typical types of disruptions: random machine failures and processing time fluctuations. Machine failures follow an exponential distribution based on the mean time between failures (*MTBF*) and the mean time to repair (*MTTR*). When a failure occurs, the corresponding machine immediately stops processing, and normal operation is resumed after repair completion. Processing time fluctuations follow a normal distribution $T_{ij} \sim N(\mu_{ij}, \sigma_{ij}^2)$, where μ_{ij} denotes the theoretical processing time of operation O_{ij}, and σ_{ij} is the fluctuation coefficient used to quantify the random deviation of processing time. Based on the above disruption characteristics, a disruption scenario set is defined as $S = \{s_1, s_2, \ldots, s_k\}$. Each scenario s_k contains four core dimensions, including disruption type, occurrence time, affected object, and impact intensity, which provide scenario support for subsequent robustness evaluation.

This study aims to achieve collaborative optimisation of efficiency, robustness, and evaluation speed, and constructs the following multi-objective optimisation function:

$$\min\left[\, \alpha \cdot \text{Makespan}(S) + \beta \cdot RI(S) + \gamma \cdot T_{eval}\right] \tag{1}$$

where, α, β, and γ are weight coefficients satisfying $\alpha + \beta + \gamma = 1$, and are used to balance the priority of different optimisation objectives. Makespan(S) represents the average completion time of all jobs under the scenario set S, which directly reflects scheduling efficiency. $RI(S)$ denotes the robustness index, defined as:

$$RI(S)=\frac{\max \text{Makespan}(s_k)}{\text{avg Makespan}(s_k)} \tag{2}$$

A smaller value of $RI(S)$ indicates stronger stability of the scheduling solution under extreme disruption scenarios and better robustness. T_{eval} represents the robustness evaluation time, which specifically quantifies the efficiency of robustness verification for scheduling solutions, addressing the limitation of traditional robust scheduling methods that focus only on efficiency and robustness while ignoring evaluation time. The design of this objective function is deeply aligned with the subsequent Transformer-driven mapping mechanism and the MC-enhanced evaluation module. By incorporating the evaluation time indicator, it directly corresponds to the core objective of "fast and high-precision robust scheduling" in this study, realizing integrated optimisation of decision performance and evaluation efficiency.

2.2 Core module: Transformer-driven disruption–performance mapper

To replace the inefficient process of repeatedly running scheduling algorithms in traditional MC simulation, an Encoder–Decoder structured Transformer is constructed to specifically learn the nonlinear mapping relationship between disruption scenarios and scheduling performance, thereby enabling rapid iteration of robustness evaluation. Fig. 1 illustrates the network architecture of the Transformer-driven disruption–performance mapper. The model architecture operates through three layers in a collaborative manner. The scenario encoding layer extracts core disruption features and transforms them into temporal sequences, covering four main dimensions: disruption type, occurrence time, affected object, and impact intensity. Among them, the disruption type is encoded using one-hot vectors, the occurrence time and impact intensity are normalized to the range [0, 1], and the affected object is represented by an index vector. All features are arranged in temporal order to form a sequence $X_S \in \mathbb{R}^{L \times d_{model}}$, where L denotes the number of disruption events in a single scenario, and d_{model} represents the feature dimension. After positional encoding is injected to incorporate temporal information, the sequence is fed into the Encoder layer. The Encoder layer consists of N Encoder blocks; each composed of a multi-head self-attention mechanism and a feed-forward neural network. The multi-head self-attention mechanism captures temporal correlations and interactions among disruption events through the following formulation:

$$\text{Attention}\,(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{3}$$

where, Q, K, and V denote the query, key, and value matrices, respectively, $d_k = d_{model}/h$, and h is the number of attention heads. The feed-forward neural network adopts two linear transformations with ReLU activation functions to enhance the model's capability in fitting complex mapping relationships. The performance prediction layer maps the Decoder output vectors through linear transformation and Sigmoid activation, directly producing a three-dimensional scheduling performance vector $\hat{Y}$, corresponding to the predicted values of makespan, tardiness rate, and robustness index, respectively, thereby realizing an end-to-end mapping from disruption scenarios to core performance indicators.

The model training strategy is designed around mapping accuracy and generalization capability. A large-scale and diversified disruption scenario dataset is generated using SimPy, covering different disruption intensities, frequencies, and types. For each scenario, a baseline scheduling algorithm is executed to obtain the ground-truth performance indicators Y, thereby constructing training sample pairs $\{(X_S, Y)\}$ and ensuring that the data distribution conforms to actual production disruption characteristics. The training process optimizes model parameters using the mean squared error loss function, defined as:

$$L = \frac{1}{N_{data}} \sum_{i=1}^{N_{data}} \left\| \hat{Y}_i - Y_i \right\|_2^2 \tag{4}$$

where, N_{data} denotes the total number of training samples. By minimizing the error between predicted values and true values, the mapping accuracy is improved. The Adam optimizer is employed with an initial learning rate set to 1×10^{-4}, which decays by 10 % every 100 epochs to balance early convergence speed and later training stability. Meanwhile, a Dropout mechanism with a probability of 0.2 is introduced to suppress overfitting, ensuring that the model can still output reliable prediction results for unseen disruption scenarios, thereby providing efficient and accurate performance prediction support for the subsequent MC-enhanced robustness evaluation.

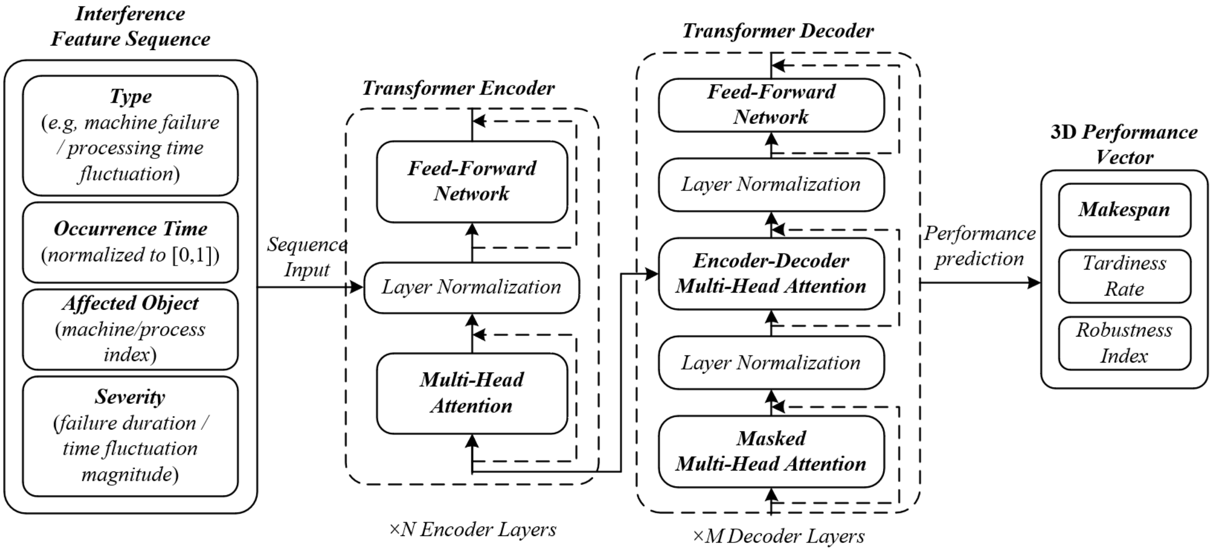


Figure 1: Transformer-driven disruption–performance mapper network architecture.

2.3 MC-enhanced robustness evaluation module

To address the problem that uniform sampling in traditional MC methods leads to insufficient coverage of high-risk scenarios and limited evaluation accuracy, this module integrates the distribution learning capability of the Transformer and designs an importance sampling-based scenario generation strategy, thereby achieving collaborative improvement in sampling efficiency and evaluation accuracy. First, the trained Transformer mapper is used to learn the probability distribution of disruption scenarios $P(S)$, accurately identifying high-risk scenarios with relatively large robustness index values and clarifying key regions for scenario sampling. Based on this, an importance sampling mechanism is constructed, assigning higher sampling weights to high-risk scenarios. The estimation formula of the robustness evaluation indicator is defined as:

$$\hat{\theta} = \frac{1}{N} \sum_{k=1}^{N} \frac{f(s_k).P_0(s_k)}{P(s_k)} \tag{5}$$

where, θ denotes the core robustness evaluation indicator, $f(s_k)$ represents the scheduling performance value corresponding to scenario s_k, $P_0(s_k)$ denotes the uniform sampling distribution adopted by traditional MC simulation, and $P(s_k)$ denotes the high-risk scenario distribution learned by the Transformer. This design significantly increases the coverage proportion of high-risk scenarios without increasing the number of samples, effectively addressing the limitation of traditional sampling methods in capturing extreme disruption scenarios and substantially enhancing the accuracy of robustness evaluation.

Based on the Transformer-driven disruption–performance mapper, a fast robustness evaluation process is constructed to completely replace the inefficient procedure of repeatedly running scheduling algorithms in traditional MC simulation. The process takes the initial scheduling solution $Schedule_0$ as input and sets the number of MC samples N to 10,000 to ensure evaluation reliability. Based on the aforementioned importance sampling strategy, N disruption scenarios are generated to fully cover different disruption characteristics and risk levels. All scenarios are then input into the trained Transformer mapper, which outputs the performance prediction value $\hat{Y}_k$ for each scenario in an end-to-end manner, avoiding the redundant computation in traditional methods that requires repeated execution of scheduling algorithms for single-scenario evaluation. Finally, the robustness index, average makespan, and tardiness rate are calculated based on $\hat{Y}_k$, completing the full robustness evaluation process. This process reduces the evaluation time complexity from the traditional $O(N \cdot T_{schedule})$ to $O(N + T_{model})$, where $T_{schedule}$ denotes the execution time of a single scheduling algorithm, and T_{model} denotes the prediction time of the Transformer model. Through the collaborative innovation of the mapper and the sampling strategy, a breakthrough improvement in robustness evaluation efficiency is achieved. Fig. 2 presents a comparison of the MC-enhanced robustness evaluation processes, where the left side shows "traditional MC evaluation" and the right-side shows "the enhanced evaluation proposed in this paper".

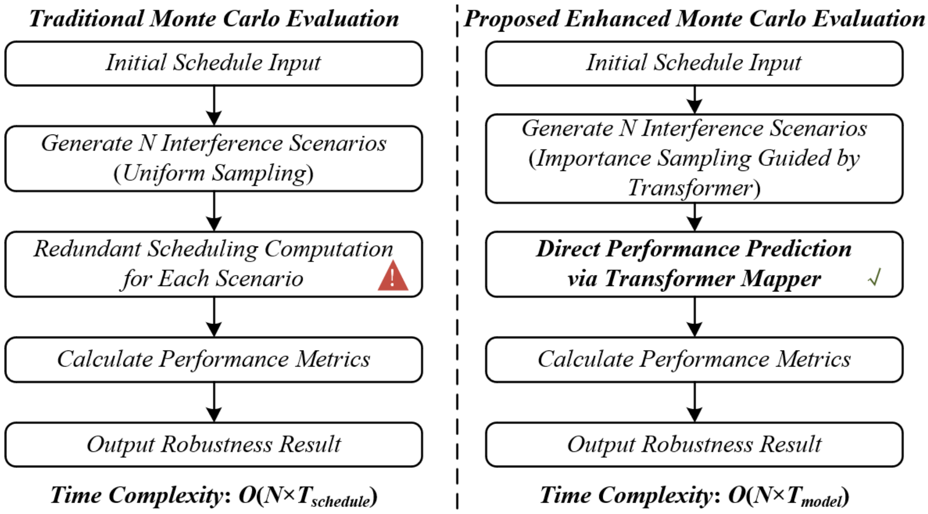


Figure 2: Comparison of MC-enhanced robustness evaluation processes.

2.4 "Decision–evaluation" collaborative training and optimisation process

A dual-layer closed-loop collaborative optimisation structure is constructed to realize deep coupling between scheduling decision-making and robustness evaluation, addressing the performance imbalance caused by their separation in traditional methods. The upper layer is a Transformer-enhanced deep reinforcement learning decision layer, whose core idea is to strengthen scheduling state representation through the encoding capability of the Transformer. Multi-dimensional information, including machine load, operation completion progress, and current disruption status, is input into a Transformer Encoder. Through the multi-head self-attention mechanism, intrinsic correlations and temporal characteristics among different state dimensions are captured, and high-dimensional feature vectors are output and injected into the value function of a deep Q-network to accurately evaluate the long-term returns of different scheduling actions, ultimately outputting optimal actions for operation assignment and processing sequence adjustment. The lower layer is the MC-enhanced robustness evaluation layer, which takes the scheduling solutions generated by the upper layer as input and rapidly outputs the robustness index and efficiency indicators, forming a feedback optimisation loop. A robustness-integrated reward function is designed to guide decision optimisation, defined as $R = R_{eff} - \lambda \cdot RI$, where R_{eff} denotes the efficiency reward based on makespan and tardiness rate, and λ is the robustness penalty coefficient. By dynamically balancing efficiency gains and robustness losses, the decision model is guided to generate scheduling solutions that simultaneously consider efficiency and stability.

The overall optimisation process is divided into three stages: pre-training, collaborative training, and online scheduling, to ensure model performance and adaptability to actual production. In the pre-training stage, the Transformer-driven disruption–performance mapper and the Transformer–DRL decision model are independently trained. The mapper fits the nonlinear relationship between disruptions and performance, while the decision model preliminarily learns basic scheduling strategies, laying a parameter foundation for subsequent collaborative training and avoiding training oscillation caused by initial parameter imbalance. In the collaborative training stage, an alternating update strategy is adopted. First, the mapper parameters are fixed, and the decision model is optimized based on robustness indicators fed back from the evaluation layer. Then, scheduling solutions generated by the optimized decision model are used as samples to fine-tune the mapper parameters to improve prediction accuracy. The two modules iterate alternately until the loss functions converge, achieving collaborative improvement of decision capability and evaluation accuracy. In the online scheduling stage, disruption information and operational states of the production system are collected in real time. The decision layer rapidly generates scheduling solutions, and the evaluation layer completes robustness verification at the millisecond level. If the robustness index exceeds a preset threshold, rescheduling is immediately triggered. Through dynamic adjustment, adaptive responses to uncertain disruptions are realized, ensuring the stable operation of the production system.

3. SIMULATION EXPERIMENTS

3.1 Simulation environment and experimental design

A discrete-event simulation system is built based on Python and SimPy to realize full-process integration and validation of the proposed scheduling framework. SimPy is responsible for simulating the core production processes of the dynamic job shop, including operation processing, machine failures, processing time fluctuations, and order arrivals, thereby accurately reproducing uncertain production scenarios. The Transformer and deep reinforcement learning models are implemented using PyTorch, while the collaborative training framework is constructed based on TensorFlow to ensure training stability and efficiency. The experimental hardware configuration includes an Intel Xeon Gold 6342 processor, an NVIDIA A100 40 GB GPU, and 128 GB of memory, providing sufficient computational support for large-scale disruption scenario simulation and complex model training. The simulation scenarios are constructed by extending the internationally recognized FT and LA series standard scheduling benchmark datasets. The number of jobs is set from 10 to 50, and each job contains 2 to 10 operations. Machine failures follow an exponential distribution, with the *MTBF* ranging from 20 to 50 hours and the *MTTR* ranging from 1 to 5 hours. Processing time fluctuations follow a normal distribution, with fluctuation coefficients set to 0.1 to 0.3 times the theoretical processing time. Order arrivals follow a Poisson distribution, with random arrival rates of 0.02 to 0.05 orders per hour, comprehensively covering typical uncertainties in dynamic production environments.

To fairly verify the superiority of the proposed method, the experimental design includes benchmark method comparison and ablation experiments, ensuring that the effectiveness of the proposed innovations can be quantitatively validated. The benchmark methods are divided into three categories. For static robust scheduling methods, robust scheduling based on stochastic programming and greedy heuristic scheduling are selected. For dynamic scheduling methods, traditional deep Q-network scheduling, Dueling deep Q-network scheduling, and genetic algorithm-based optimized scheduling are included. These two categories represent traditional and existing advanced scheduling techniques, respectively, ensuring the comprehensiveness of the comparison. Two control groups are designed for the ablation experiments. One group removes the Transformer-driven disruption–performance mapper and retains only MC simulation, while the other group retains both the Transformer and MC simulation but removes the importance sampling mechanism. By comparing their performance differences with the proposed method, the role of the mapper in improving evaluation efficiency and the effect of importance sampling on enhancing evaluation accuracy are respectively verified, providing direct experimental support for the core innovations.

3.2 Simulation results and analysis

The experiments are conducted under three levels of disruption intensity: low, medium, and high. Low disruption corresponds to a processing time fluctuation coefficient of 0.1 and an order arrival rate of 0.02. Medium disruption corresponds to a fluctuation coefficient of 0.2 and an order arrival rate of 0.035. High disruption corresponds to a fluctuation coefficient of 0.3 and an order arrival rate of 0.05. Dynamic scheduling methods are selected as baselines and compared with the proposed method. The mean values and standard deviations of the core performance indicators are shown in Table I, comprehensively quantifying scheduling efficiency, stability, and evaluation speed.

Table I: Performance comparison of different scheduling methods.

Method category	**Specific method**	**Disruption intensity**	**Average makespan** (h) ± ***std***	**Robustness index (*RI*)** ± ***std***	**Evaluation time** (s) ± ***std***	**Worst-case makespan** (h)
Dynamic scheduling	Traditional DQN scheduling	Low	78.9±3.3	1.31±0.08	46.2±4.4	102.1
		Medium	98.8±5.6	1.52±0.11	69.7±5.9	148.5
		High	140.2±8.9	1.75±0.15	93.8±7.6	242.1
	Dueling DQN scheduling (Duelling DQN)	Low	75.7±3.0	1.24±0.07	53.1±4.9	95.3
		Medium	93.7±4.9	1.41±0.10	77.5±6.5	136.8
		High	134.5±8.3	1.68±0.14	107.2±8.4	223.9
	Genetic algorithm-based scheduling (GA-RS)	Low	77.4±3.2	1.28±0.08	64.5±5.7	100.1
		Medium	95.5±5.2	1.45±0.11	90.3±7.3	143.2
		High	137.1±8.5	1.71±0.14	122.8±9.5	229.4
Proposed Method	Transformer + MC simulation	Low	72.9±2.7	1.21±0.06	51.8±4.7	91.0
		Medium	81.8±4.2	1.13±0.09	75.2±6.3	109.8
		High	112.1±7.3	1.27±0.12	100.3±8.0	157.6

As shown in Table I, among the dynamic scheduling methods, Dueling DQN achieves the best performance; however, under high disruption intensity, its average makespan still reaches 134.5 h with a robustness index of 1.68. The proposed method demonstrates prominent advantages across all disruption intensity levels, with particularly significant performance improvements under medium and high disruption conditions. Under medium disruption, the average makespan is reduced by 12.7 % and the robustness index is reduced by 20.0 % compared with Dueling DQN. Under high disruption, the average makespan is reduced by 16.7 % and the robustness index is reduced by 24.4 %. These results fully verify the integrated optimisation effect of the collaborative mechanism between the Transformer and MC simulation.

To quantify the independent contributions of the core innovation modules, two ablation control groups are designed by removing the Transformer mapper and the importance sampling mechanism, respectively. The performance comparison results of each group are shown in Table II.

Table II: Performance comparison of ablation experiment groups.

Method	**Disruption intensity**	**Average makespan** (h) ± *std*	**Robustness index (*RI*)** ± *std*	**Evaluation time** (s) ± *std*	**Worst-case makespan** (h)
MC only	Low	77.8±3.1	1.32±0.08	172.3±13.8	101.5
	Medium	97.2±5.1	1.55±0.12	251.3±20.1	151.2
	High	138.9±8.4	1.86±0.16	335.6±25.2	249.8
Transformer + MC-UNIF	Low	75.3±2.9	1.26±0.07	59.1±5.3	97.8
	Medium	91.6±4.7	1.44±0.10	83.9±7.0	145.1
	High	131.2±7.9	1.74±0.15	114.1±9.1	250.5
Proposed method	Low	72.9±2.7	1.21±0.06	51.8±4.7	91.0
	Medium	81.8±4.2	1.13±0.09	75.2±6.3	109.8
	High	112.1±7.3	1.27±0.12	100.3±8.0	157.6

After removing the Transformer mapper, MC-only needs to repeatedly execute the scheduling algorithm to complete scenario evaluation. Under all disruption intensity levels, the evaluation time of MC-only is 2.68 to 3.34 times that of the proposed method. Under medium disruption, the evaluation time of MC-only reaches 251.3 s, while the proposed method requires only 75.2 s. At the same time, the robustness index of MC-only is 37.2 % higher than that of the proposed method, verifying the core role of the Transformer mapper in improving evaluation efficiency and robustness optimisation accuracy. After removing the importance sampling mechanism, Transformer + MC-UNIF adopts a uniform sampling strategy. Its worst-case makespan under medium and high disruption is 32.2 % and 59.0 % higher than that of the proposed method, respectively, and the robustness index is 27.4 % and 36.9 % higher, respectively. This difference originates from the difficulty of uniform sampling in focusing on high-risk scenarios, whereas importance sampling guided by the disruption distribution learned by the Transformer strengthens the coverage of high-risk scenarios, proving the critical value of this sampling strategy in improving robustness evaluation accuracy. The results of the two types of ablation experiments indicate that the core components of the proposed method are mutually collaborative and indispensable, jointly supporting efficient and high-precision robust scheduling performance.

Representative static scheduling method SP-RS, representative dynamic scheduling method Dueling DQN, and the proposed method are selected to analyse the variation trend of the robustness index with disruption intensity. The results are shown in Table III.

Table III: Variation of robustness index with disruption intensity for typical methods.

Method	**Low disruption (*RI*)**	**Medium disruption (*RI*)**	**High disruption (*RI*)**	**Increase from low to high** (%)
Stochastic programming–based robust scheduling (SP-RS)	1.35	1.62	1.93	42.9
Dueling DQN	1.24	1.41	1.68	35.5
Proposed method	1.21	1.13	1.27	4.9

As shown in Table III, the impact of disruption intensity on the performance of different methods exhibits significant differences. The robustness index of static methods and traditional dynamic methods increases approximately linearly with increasing disruption intensity, with an increase of 42.9 % for SP-RS and 35.5 % for Dueling DQN. In contrast, the performance degradation rate of the proposed method is significantly lower, with the robustness index increasing by only 4.9 %. Under high disruption, the robustness index of the proposed method is 34.2 % lower than that of SP-RS and 24.4 % lower than that of Dueling

DQN, reflecting strong adaptability to complex disruption environments. This advantage mainly originates from the accurate characterization of the disruption–performance relationship by the Transformer and the efficient risk evaluation enabled by MC simulation.

Under fixed high disruption intensity and fixed Transformer parameters (number of attention heads $h = 8$, number of Encoder layers $N = 6$), different sampling numbers are set to analyse their impact on the performance of the proposed method. The results are shown in Table IV.

Table IV: Effect of sampling number on the performance of the proposed method (high disruption intensity).

Sampling number	**Robustness index (*RI*) ± *std***	**Average makespan** (h) ± ***std***	**Evaluation time** (s) ± ***std***
2000	1.52±0.14	128.6±8.1	45.7±3.9
5000	1.27±0.12	115.3±7.5	78.9±6.5
8000	1.25±0.12	113.5±7.4	92.4±7.3
10000	1.27±0.12	112.1±7.3	100.3±8.0
12000	1.26±0.12	111.8±7.3	115.6±8.7

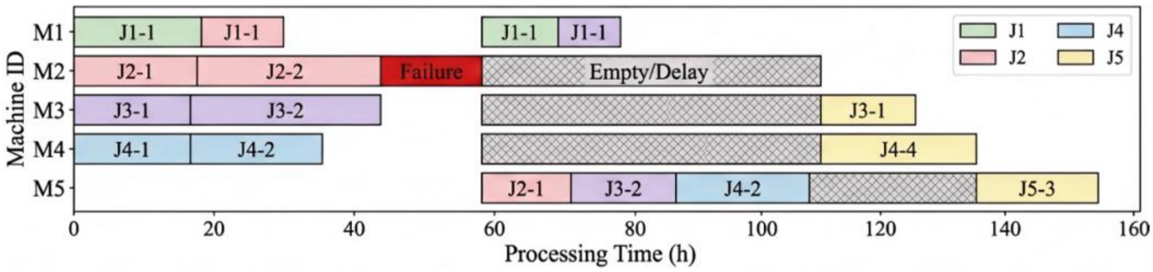
When the sampling number is lower than 5000, the robustness index decreases rapidly with increasing sampling number. At 2000 samples, the *RI* reaches 1.52, and at 5000 samples it decreases to 1.27, with a reduction of 16.4 %. When the sampling number is greater than or equal to 5000, the robustness index tends to stabilize. The *RI* difference between 8000 and 12000 samples is only 0.01, and the fluctuation in average makespan is less than 0.3 h. Meanwhile, even when the sampling number reaches 10,000, the evaluation time of the proposed method is only 100.3 s, which is 55.2 % lower than the 335.6 s of MC-only. This indicates that the proposed method can achieve high-precision robustness evaluation with a limited number of samples, demonstrating efficiency advantages for practical production applications.

A parameter sensitivity analysis is conducted for the number of Attention heads h and the number of Encoder layers N of the Transformer. Under fixed high disruption intensity and a sampling number of 10,000, the results are shown in Table V.

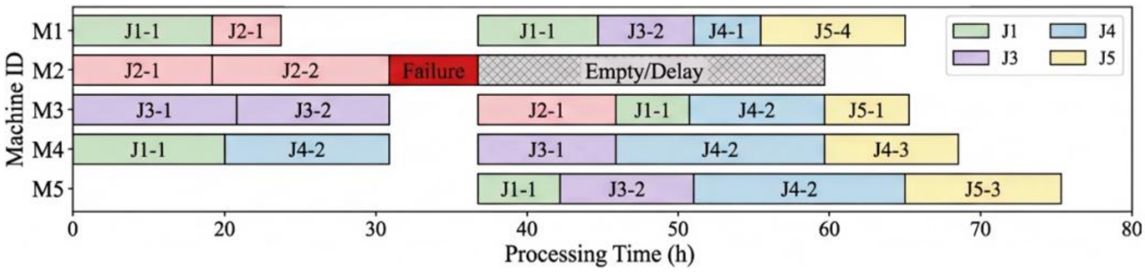
Table V: Effects of Transformer model parameters on performance (high disruption intensity, sampling times = 10000).

Number of Attention heads (h)	**Number of Encoder layers (*N*)**	**Robustness index (*RI*)**	**Average completion time** (h)	**Model training time** (min)
4	4	1.38	121.5	28.6
4	6	1.33	117.2	42.9
6	4	1.31	116.8	41.5
6	6	1.29	114.2	63.2
8	4	1.28	113.5	62.8
8	6	1.27	112.1	94.5
8	7	1.26	111.9	112.3
10	6	1.26	111.8	131.7

When the parameter combination is $h = 8$ and $N = 6$, the model performance is optimal, with a robustness index of 1.27 and an average completion time of 112.1 h. When the parameters are further increased, the robustness index and average completion time are only improved by 0.79 % and 0.18 %, respectively, while the model training time increases by 39.4 % and 18.8 %, leading to a significant rise in computational cost. If the parameter configuration is too low, the robustness index decreases by 8.7 % and the average completion time increases by 8.4 %, indicating insufficient feature extraction and temporal correlation capturing capability. Therefore, h = 8 and N = 6 represent the optimal parameter configuration that balances performance and cost, which can provide a reference for subsequent engineering implementation.



a) Baseline Dueling DQN



b) Proposed method

Figure 3: Comparison of scheduling Gantt charts under typical disruption scenarios.

In order to intuitively illustrate the adaptive response mechanism of the proposed framework under sudden disruptions, this study selects a machine random failure scenario for comparative case analysis. As shown in Fig. 3, the baseline Dueling DQN method exhibits obvious passive waiting characteristics after the failure occurs. Due to the lack of risk anticipation and dynamic global resource scheduling capability, the blocked operations generate significant idle time windows and lead to cascading delay effects in downstream operations. In contrast, the proposed Transformer-driven method can rapidly identify disruption characteristics and trigger rescheduling decisions, flexibly transferring affected operations to other available machines, effectively compressing production gaps and smoothing disturbance fluctuations. This proactive intervention mechanism significantly shortens the final completion time compared with the baseline method, visually confirming that the deep integration of sequence modelling and MC-enhanced risk evaluation can effectively improve the resilience and continuity of production systems under uncertain environments.

4. CONCLUSIONS AND FUTURE WORK

Aiming at the uncertainty disruption problem in dynamic job shop scheduling, this paper proposed an adaptive robust scheduling method integrating Transformer and MC simulation and constructed an efficient and high-precision scheduling system through three core innovations. A Transformer-driven disruption–performance mapping mechanism was constructed to replace the redundant process of repeatedly running scheduling algorithms in traditional MC simulation, breaking through the efficiency bottleneck of robustness evaluation and realizing fast end-to-end prediction from disruption scenarios to scheduling performance. A decision–evaluation collaborative optimisation framework was established, deeply integrating the adaptive decision-making capability of Transformer-enhanced deep reinforcement learning and the risk evaluation advantages of MC simulation. Through a robustness-integrated reward function, a dynamic balance between scheduling efficiency and stability was guided. Production simulation experiments show that, under medium and high disruption scenarios, the proposed method significantly reduced completion time and robustness index compared with existing advanced dynamic scheduling methods, while greatly shortening evaluation time. This provides a new technical path for intelligent robust scheduling in the field of production simulation, enriches the research system of collaborative optimisation between sequence modelling and risk evaluation in uncertainty scheduling, and has important academic value and engineering reference significance.

However, this study still has several limitations, and industrial deployment faces multiple challenges. The current experiments are based on extended scenarios of standard benchmark datasets, and the generalization capability of the model in complex industrial scenarios such as multi-shop collaboration and heterogeneous machines still needs further verification. The training of the Transformer model relies on high-performance computing resources, making it difficult to be directly deployed on industrial on-site edge devices. Although evaluation efficiency is significantly improved, the real-time rescheduling response speed under high disruption scenarios still needs to be optimized to adapt to actual production rhythms. In response to the above issues, future work will be promoted from four aspects: integrating digital twin technology to construct a virtual–real interactive scheduling framework to achieve accurate disruption prediction and online optimisation of solutions; introducing incremental learning algorithms to enhance model adaptability and improve generalization performance in complex scenarios; expanding optimisation objectives such as energy consumption and cost to build a multi-objective robust scheduling system that fits industrial practical requirements; and reducing computational resource consumption through model pruning and quantization, promoting the deployment and application of the proposed method on industrial edge devices.

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