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ENHANCING PRODUCTION EFFICIENCY THROUGH SMART SCHEDULING: A DEEP LEARNING AND SIMULATION-BASED APPROACH

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Abstract. *Production scheduling in complex manufacturing environments presents significant challenges due to dynamic conditions, intricate task dependencies, limited resource availability, and unplanned disruptions such as machine failures or workforce shortages. Traditional rule-based scheduling systems often lack the flexibility to adapt to these evolving constraints, resulting in suboptimal performance. To address this, we propose a novel "smart scheduling" framework that integrates deep learning (DL), reinforcement learning (RL), agent-based simulation (ABS), and discrete event simulation (DES). This hybrid approach enhances scheduling responsiveness and efficiency by enabling predictive, adaptive, and autonomous decision-making. In the proposed system, a DL model is trained on historical production data to accurately predict task durations, improving the precision of scheduling inputs. RL acts as the decision-making core, dynamically optimizing scheduling policies in real time to minimize makespan and maximize resource utilization. ABS models the behaviors and interactions of individual agents such as machines and operators, while DES captures the overall process flow and event sequences on the production line. The integrated framework was evaluated across multiple operational scenarios, including standard conditions, machine breakdowns, and workforce reductions. Experimental results demonstrate that the smart scheduling system consistently outperforms conventional rule-based approaches, achieving up to a 20% reduction in makespan and significant improvements in resource utilization. These findings underscore the potential of AI-driven, simulation-enhanced scheduling to improve resilience, adaptability, and operational efficiency in modern manufacturing environments, supporting broader efforts in industrial innovation and sustainable production.*

Keywords: Production scheduling, Smart scheduling, Deep learning, Reinforcement learning, Agent-based simulation, Discrete event simulation

1. **Introduction.** Production scheduling plays a critical role in enhancing operational efficiency in modern manufacturing, particularly within complex, multi-product assembly environments [1,2]. These systems are inherently dynamic, characterized by interdependent tasks, constrained resources, and frequent disruptions such as machine breakdowns or workforce shortages [3,4]. Traditional rule-based scheduling approaches often lack the flexibility to adapt to such variability, leading to inefficiencies and suboptimal outcomes [3].

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Recent advancements in artificial intelligence (AI) and smart manufacturing have motivated researchers to adopt more adaptive and data-driven scheduling methods. In particular, deep learning (DL) has demonstrated strong capabilities in predicting task durations, machine behavior, and production-related variables with high accuracy [5]. Reinforcement learning (RL) has gained traction as a decision-making mechanism for dynamic scheduling, outperforming heuristic and rule-based approaches in complex job-shop and flow-shop environments [6-9]. Moreover, hybrid AI frameworks, such as those integrating attention mechanisms, graph neural networks (GNNs), digital twins, and multi-agent learning, have recently emerged as promising directions for improving production resilience and real-time adaptability [10-12].

Simulation techniques continue to serve as essential tools for modeling real-world manufacturing systems. Agent-based simulation (ABS) effectively captures the behavioral diversity and interactions among machines, workers, and transport systems [13], while discrete event simulation (DES) provides a robust foundation for modeling the sequence of operations and system-level temporal dynamics [14]. Despite substantial progress, recent literature still lacks a unified framework that integrates DL-based prediction, RL-based control, and hybrid ABS-DES simulation into a cohesive system capable of supporting both predictive and reactive scheduling in real time.

This research seeks to address that gap by proposing a unified *"smart scheduling"* framework that combines DL, ABS, DES, and RL. DL enhances prediction accuracy by learning task duration patterns from historical data. RL enables adaptive, real-time scheduling decisions that react to evolving operational conditions. Meanwhile, the integration of ABS and DES provides a realistic modeling environment that captures both micro-level agent behaviors and macro-level event flows.

The primary objective of this study is to develop and evaluate an integrated scheduling approach that 1) minimizes makespan, 2) maximizes resource utilization, and 3) improves adaptability to dynamic disruptions. Unlike prior studies that focus on one or two techniques in isolation, the proposed framework leverages the complementary strengths of DL, RL, and hybrid simulation to deliver a more comprehensive and resilient scheduling system. To validate the proposed system, simulations were conducted under three realistic manufacturing scenarios: Baseline Operation, High Demand with Machine Breakdown, and Reduced Workforce Availability. The results show that the smart scheduling system consistently outperforms traditional rule-based approaches, demonstrating substantial improvements in makespan and resource utilization. These findings highlight the practical potential of AI-driven, simulation-enhanced scheduling systems to support more adaptive and efficient Industry 4.0 environments.

The remainder of this paper is structured as follows. Section 2 details the proposed methodology. Section 3 presents the simulation results and comparative analysis. Section 4 concludes the study and discusses future research directions.

2. **Methodology.**

In production scheduling, the primary objective is to minimize the makespan $C_{\max}$, which represents the total time required to complete all tasks within the production schedule. Reducing $C_{\max}$ directly contributes to increasing production throughput and improving delivery performance [1,4,5]. Achieving this objective, however, is challenging because the scheduler must ensure efficient resource utilization while satisfying several constraints, including task assignment, resource capacity, and task precedence.

To achieve adaptive and efficient production scheduling in complex manufacturing environments, this study proposes an integrated framework combining DL for task prediction, RL for dynamic scheduling, and simulation techniques including ABS and DES for system modeling. The overall methodology is depicted in Figure 1.

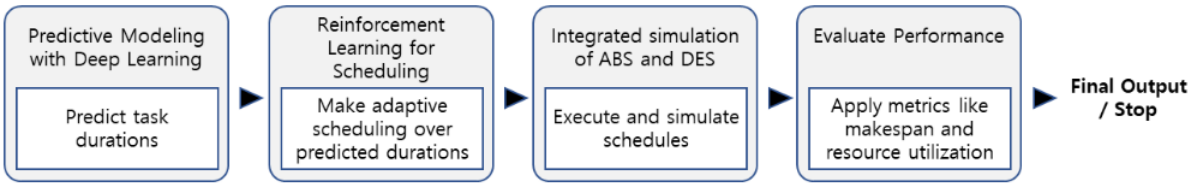


FIGURE 1. Research methodology

2.1. **Predictive modeling for task duration prediction with DL.** Accurate task duration prediction is critical for effective scheduling [7,8]. This study employed supervised learning using a feedforward neural network trained on historical production data. Early stopping and dropout regularization were applied to preventing overfitting. Each input sample consisted of features such as task type, machine specifications, operator skill level, and prior completion times. The target output was the actual duration of the task. The model was trained to minimize the mean squared error (MSE) loss function, defined as presented in Equation (1).

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(\hat{t}_i - t_i\right)^2 \tag{1}$$

where $\hat{t}_i$ is the predicted duration and t_i is the actual duration.

This study applied early stopping and dropout regularization to preventing overfitting and validated the model using k-fold cross-validation. The trained model outputs were used as input to the simulation and scheduling layers, enabling dynamic scheduling decisions based on real-time task predictions.

2.2. **RL for dynamic scheduling.** To adaptively schedule tasks under dynamic conditions [9-15], we modeled the RL component models scheduling as a Markov decision process (MDP):

1) State (s_t): Encodes the current system state, including queue length, resource availability, and predicted task durations;
2) Action (a_t): Represents assigning a task to a specific machine or resource at time t;
3) Reward (r_t): A composite metric that penalizes idle time and long makespan, defined as

$$r_t = -\left(\alpha \cdot Makespan + \beta \cdot IdleTime\right) \tag{2}$$

where α and β are hyperparameters balancing objectives.

The RL agent seeks to learn an optimal policy π^*, maximizing the expected discounted return over a scheduling horizon T:

$$\pi^*(s) = \arg\max_{\pi} E\left[\sum_{t=0}^{T}\gamma^t r_t\right] \tag{3}$$

where $\gamma \in (0,1)$ is the discount factor. We implemented proximal policy optimization (PPO) due to its stability and sample efficiency in complex, high dimensional environments. The RL component was trained in a simulated environment generated via DES and ABS, ensuring the agent learns from realistic production dynamics.

2.3. **Integration of ABS and DES.** To model the factory floor environment in detail, we integrated **ABS** and **DES**.

- **ABS Layer:** Models individual agents such as machines, human operators, and mobile robots [16]. Each agent follows its own set of rules and behaviors, including

task acceptance, failure probability, and rest cycles. Agents also interact, enabling decentralized coordination and emergent behavior.

- **DES Layer:** Controls the overall flow of events in the production system, such as task initiation, task completion, machine breakdowns, and resource releases [17]. The DES environment tracks global system time and orchestrates event execution.

The interaction between ABS and DES ensures that local behaviors (e.g., machine decision-making) are synchronized with global scheduling events. Feedback from the ABS layer (e.g., agent state changes or failures) informs the RL scheduler in real time, enabling rapid adaptation to disruptions or performance deviations.

2.4. **System workflow.** To operationalize the proposed smart scheduling framework, the system is structured into four interconnected layers that collectively enable data-driven, adaptive decision-making in dynamic production environments [16-19].

1) **Input Layer:** Historical data is fed into the deep learning model to generate duration predictions.
2) **Simulation Layer:** DES schedules the macro-events and controls the simulation clock, while ABS simulates micro-level behaviors.
3) **Decision Layer:** The RL agent observes the simulation state and adjusts scheduling decisions dynamically.
4) **Evaluation Layer:** Performance metrics (e.g., makespan, and resource utilization) are computed to assess system efficiency and guide policy updates.

This integrated design facilitates a closed-loop learning and scheduling process where the system continuously adapts to changing operational conditions.

3. **Simulation Results and Discussion.** This section presents the simulation results and performance analysis of the proposed smart scheduling system across various operational scenarios, highlighting its effectiveness compared to traditional rule-based approaches.

3.1. **Experimental setup.** To evaluate the performance of the proposed smart scheduling framework, we designed three simulation scenarios that represent common and critical conditions in a modern manufacturing environment. These scenarios were implemented using a DES engine, with embedded agent-based behaviors and real-time decision-making driven by RL. The experiments used a synthetic dataset modeled after a multi-product assembly line, consisting of task sequences, machine capabilities, and operator availability, based on operational characteristics of a light metal manufacturing company in Surabaya, Indonesia, as Southeast Asia's largest flat-rolled aluminum manufacturer, involving complex production scheduling to manage various aluminum products and machinery.

The dataset included 50 unique tasks with varied processing durations, machine requirements, and precedence constraints. Each task entry was represented as shown in Table 1. Each simulation run covered a full production shift of 480 minutes, with the system

Table 1. Part of dataset involved in this study

Task ID	Product type	Machine type	Operator skill	Base duration (min)	Precedence task
T01	A	CNC-1	Skilled	8.5	–
T02	A	CNC-2	Semi-skilled	10.0	T01
T03	B	Paint-1	Skilled	12.5	–
T04	B	Robot-Arm	Skilled	7.5	T03
...	...	...	...	...	...

scheduled either using 1) traditional rule-based method (first-come-first-serve, FCFS) or 2) smart scheduling system.

The three scenarios evaluated were

1) **Scenario 1** – Baseline Operation: Regular task flow without major disruptions, full workforce and machine availability;
2) **Scenario 2** – High Demand with Machine Breakdown: 30% increase in task load; random breakdowns simulated for 20% of the machines;
3) **Scenario 3** – Reduced Workforce Availability: 25% reduction in available operators, simulating labor shortages or shift conflicts.

The smart scheduling system used predicted task durations from the trained neural network and dynamically adjusted schedules using the PPO of the RL algorithm. Agents in the ABS component modeled machines and workers reacting to real-time changes.

3.2. **Results and analysis.** The performance of the smart scheduling system was compared against the FCFS baseline across the three defined scenarios. Key performance indicators (KPIs) included two key metrics: makespan (total time to complete all tasks) reduction and resource utilization (percentage of machine and operator time spent on productive tasks) improvement. The results are summarized in Table 2.

Table 2. Simulation results

Scenario	Makespan reduction	Resource utilization increase	Remarks
Baseline Operation	15%	10%	Smooth production flow with fewer idle times
High Demand + Machine Breakdown	20%	13%	Superior recovery from disruptions and rerouting
Reduced Workforce Availability	12%	8%	Adaptive load balancing under constrained human resources

During the scheduling process, the system enforces fundamental constraints, where each task must be assigned exactly once, and no resource may exceed its available capacity. These constraints are consistently maintained by both the rule-based and smart scheduling systems throughout the simulation. The smart scheduler integrates Equation (1) during the prediction phase to generate accurate task duration estimates, and it applies these constraint checks during task allocation. Subsequently, Equation (3) is used to optimize scheduling decisions in real time through the RL. Together, these steps enable the scheduler to enhance production speed and efficiency, ensuring an end-to-end optimization workflow across all stages of the system. The simulation results demonstrate that the integrated AI-based scheduler can intelligently adjust task assignments in real time, significantly improving performance over static rule-based systems. In the *High Demand with Machine Breakdown* scenario, the scheduler successfully rerouted tasks to available machines while maintaining precedence and reducing idle time, whereas in the *Reduced Workforce Availability* scenario, it redistributed workloads to prevent bottlenecks. These outcomes highlight the system's robustness in managing both predictable and unpredictable disruptions across diverse operational conditions.

Across all scenarios, the smart scheduler consistently reduced makespan, by 15% during *Baseline Operation*, 20% under *High Demand with Machine Breakdown*, and 12% with *Reduced Workforce Availability*, demonstrating improved throughput and adaptability. Resource utilization also increased, rising by 10%, 13%, and 8%, respectively, reflecting more effective use of machines and operators even under constrained conditions. These

improvements confirm the capability of the integrated framework to minimize downtime, enhance productivity, and maintain efficient operations in dynamic manufacturing environments.

Figure 2 further illustrates the superiority of the DL-enhanced smart scheduling system compared to the traditional rule-based approach in both makespan reduction and resource utilization across all scenarios. These gains are enabled by DL for accurate task duration prediction, RL for dynamic optimization, and the ABS-DES hybrid simulation for realistic system modeling. The results align with prior studies such as [20] and [21], yet differ by offering a unified framework that integrates DL, RL, ABS, and DES into a closed-loop, intelligent scheduling system designed for complex, real-time manufacturing environments.

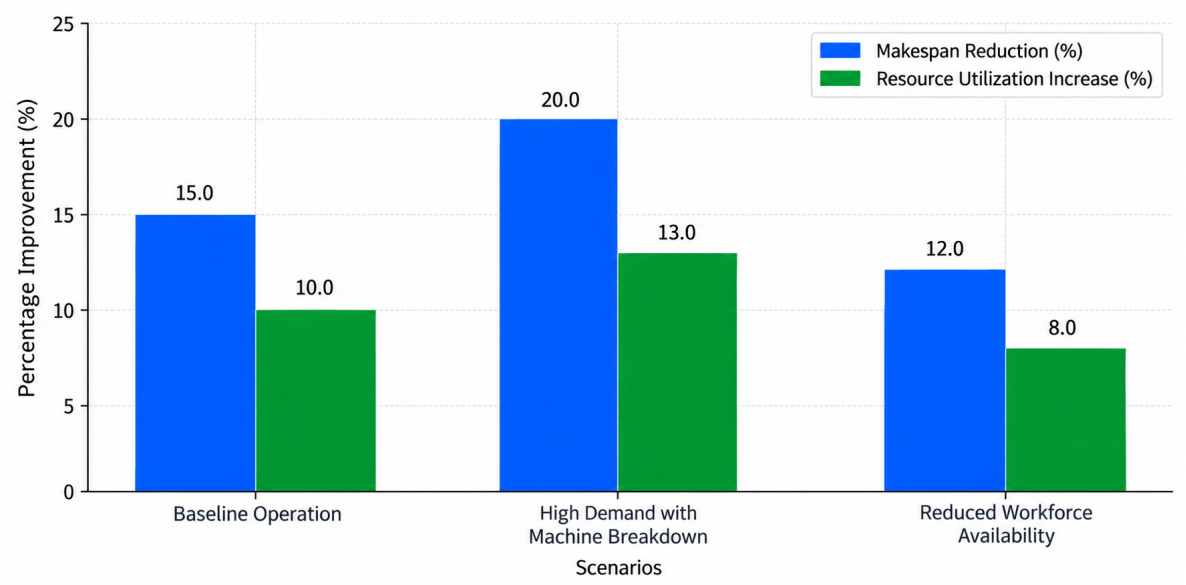


FIGURE 2. Performance evaluation of deep learning-enhanced smart scheduling system and traditional rule-based approach

To strengthen the evaluation, we included a comparative discussion with several state-of-the-art scheduling techniques reported in recent literature. Studies such as DRL-based dispatching [9-12], attention-based hybrid schedulers [14], and GNN-RL schedulers [18] demonstrate performance improvements between 10-25% in makespan reduction. Our system achieved up to 20% reduction, placing it within the upper range of reported improvements. While direct implementation-based replication of these methods is beyond the current study scope, the observed performance aligns with and in some cases exceeds state-of-the-art benchmarks.

Although this research primarily relies on simulation, the modeling assumptions (task characteristics, operator skills, machine constraints) were derived from an actual metal manufacturing company. Future work will incorporate real shop-floor event logs and operational traces to validate the learned scheduling policies in empirical deployments. Initial discussions with the partner company indicate interest in pilot testing the scheduling prototype.

4. **Conclusions.** This study proposed a smart scheduling framework integrating the DL, RL, ABS, and DES to enhance production efficiency in complex manufacturing environments. Experiments across three operational scenarios demonstrated that the system consistently outperformed traditional rule-based scheduling, achieving up to a 20% reduction in makespan and a 13% increase in resource utilization. The synergy between DL-based prediction, RL-driven adaptive decision-making, and hybrid ABS-DES modeling enabled realistic and resilient scheduling capable of responding to real-time disruptions. Despite

these strengths, the framework remains limited by its dependency on simulation fidelity, scalability challenges in large job-shop settings, reliance on high-quality training data, and its current focus on single-objective optimization.

Future work will address these limitations through multi-objective scheduling, scalable RL architectures, data-efficient learning techniques, and validation using real industrial datasets and live shop-floor deployments.

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