Curiosity-Driven Reinforcement Learning for Dynamic Flexible Job Shop Scheduling

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***Abstract*—The dynamic flexible job shop scheduling (DFJSP) problem involves assigning appropriate jobs to available machines in real time under uncertain conditions. Reinforcement learning (RL) approaches hold promise for adaptive scheduling but often suffers from sample inefficiency due to sparse and delayed rewards. This paper proposes a curiosity-driven RL framework for the DFJSP with stochastic job arrivals. A centralized policy sequentially activates machines to select jobs with the objective of minimizing total tardiness. The curiosity-based intrinsic reward is incorporated to alleviate the exploration deficiency by encouraging the agent to explore novel and informative states. This intrinsic motivation improves sample efficiency in dynamic and sparse-rewards environments. The performance gain depends on scenario characteristics: it is particularly pronounced in high-load, dynamic environments, while in low-load, more predictable settings, improvements are moderate. These findings highlight the framework's potential for adaptive, data-efficient scheduling under uncertainty.**

***Index Terms*—Dynamic Flexible Job Shop Scheduling, Reinforcement Learning, Intrinsic Motivation, Curiosity-Driven Learning, Stochastic Job Arrivals**

I. Introduction

The Dynamic Flexible Job Shop Scheduling Problem (DFJSP) is a challenging combinatorial optimization problem in modern manufacturing systems [1]. Extending the classical Job Shop Scheduling Problem (JSSP), DFJSP adds flexibility—allowing each operation to be processed on multiple alternative machines—and dynamism—capturing stochastic factors such as random job arrivals and environmental uncertainties [2], [3]. These features make DFJSP NP-hard and time-dependent, rendering traditional heuristics and mathematical optimization methods computationally intractable [4].

In recent years, Reinforcement Learning (RL), particularly Deep Reinforcement Learning (DRL), has emerged as a promising paradigm for adaptive and data-driven scheduling [5]. By formulating the scheduling process as a Markov Decision Process (MDP), an RL agent can learn a mapping from system states (e.g., machine conditions, job queues) to actions (e.g., selecting which job to process) through interaction with the environment. This framework enables the discovery of effective scheduling policies that adapt to dynamic and stochastic conditions without relying on handcrafted rules or explicit system modeling [6]. However, applying RL to DFJSP remains sample-inefficient exploration due to the sparse and delayed reward problem inherent in scheduling tasks [7].

In most DFJSP settings, the primary objective—such as minimizing total tardiness or makespan—can only be measured after all jobs have been completed. Consequently, the agent receives a single terminal reward after a long sequence of scheduling decisions [8]. This results in sparse and delayed feedback, making it difficult to assign credit to individual actions that contributed to the final performance [9]. The weak and noisy learning signal reduces sample efficiency, slows convergence, and often leads to unstable or suboptimal policies [10]. In effect, the agent must navigate a vast decision space with little intermediate guidance.

To alleviate this challenge, various techniques have been proposed. Reward shaping [11] is one of the most common strategies, in which domain-specific dense rewards are manually designed to provide more frequent feedback. For instance, intermediate rewards may be based on reductions in idle time or operation delay to encourage efficient resource utilization [12]. Although such approaches can accelerate learning, they heavily rely on expert knowledge, and a poorly designed reward function can bias the learning process toward locally optimal but globally suboptimal solutions [7].

This paper proposes a curiosity-driven reinforcement learning framework for DFJSP with stochastic job arrivals. The agent operates from a machine-centric perspective, sequentially selecting which job each available machine should process next, and leverages a curiosity-based intrinsic reward to encourage exploration toward novel and informative scheduling states.

Comprehensive experiments on six DFJSP scenarios show that incorporating intrinsic motivation consistently improves total tardiness and accelerates convergence compared to a baseline agent. The benefits are especially pronounced under highly dynamic conditions with larger job counts or higher arrival rates. These observations highlight the effectiveness of curiosity-driven exploration in overcoming sparse reward challenges and suggest a promising direction for developing more autonomous and adaptable intelligent scheduling systems

II. Methodology

A. Problem Formulation

The DFJSP with stochastic job arrivals is defined as follows. A set of jobs $J = \{J_1, J_2, \ldots, J_n\}$ arrives over time and must

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be processed on a set of machines $M = \{M_1, M_2, \ldots, M_m\}$. Each job J_i consists of N_i operations $O_{i,j}$, each executable on one of several alternative machines $M_{i,j} \subseteq M$ with processing time $t_{i,j,k}$ on machine M_k. Each job has an arrival time a_i, due date d_i, and completion time C_i. The objective is to minimize total tardiness:

$$\text{Minimize} \sum_{i=1}^{n} \max\{C_i - d_i, 0\} \tag{1}$$

To ensure feasibility, the following constraints must be satisfied: 1)Each machine processes at most one operation at any time; 2)Operations of each job follow a fixed order; 3)Once started, an operation runs to completion; 4)Setup, transfer, and decision delays are ignored;

B. Reinforcement Learning Formulation

The DFJSP is formulated as an MDP (S, A, P, r, γ). At each decision step t, a centralized agent selects a job for an active machine. If multiple machines become idle simultaneously, one is randomly chosen to make a decision, ensuring a sequential and conflict-free scheduling process.

The state $s_t \in S$ comprises local features, which describe the immediate decision context, and global features, which capture the overall system status. A detailed breakdown of the features constituting the state vector is presented in Table I. The action $a_t \in A$ corresponds to selecting one job

TABLE I: State features for the scheduling agent.

Category	Feature	Description
Local	O_{rem}	Remaining operations for each candidate job
	T_{rem}	Remaining processing time for each candidate job
	T_{slack}	Slack time: due date minus remaining processing time
	U_m	Current machine utilization
Global	$\mu_{T_{rem}}$	Mean remaining processing time of all unfinished jobs
	$\sigma_{T_{rem}}$	Std. deviation of remaining processing time
	μ_{U_M}	Mean machine utilization
	σ_{U_M}	Std. deviation of machine utilization

from a dynamically constructed candidate set, described in Subsection II-C. After execution, the agent receives a reward, described in Subsection II-D. An overview is shown in Fig .1.

C. Action Masking and Candidate Generation

At each decision step, the active machine m determines the set of jobs that are eligible for its next processing operation. To structure the action space, four classical priority dispatching rules (PDRs)–Earliest Due Date (EDD), Critical Ratio (CR), Shortest Processing Time (SPT), and Minimum Slack (MS)– are used to rank the available jobs. Each rule contributes its highest-ranked job that is not already included in the candidate pool $\mathcal{C}$, proceeding down the ranking if necessary to avoid duplicates. This process yields at most four distinct candidate actions. If fewer than four candidates are obtained, dummy masked actions are added to ensure a fixed action dimension.

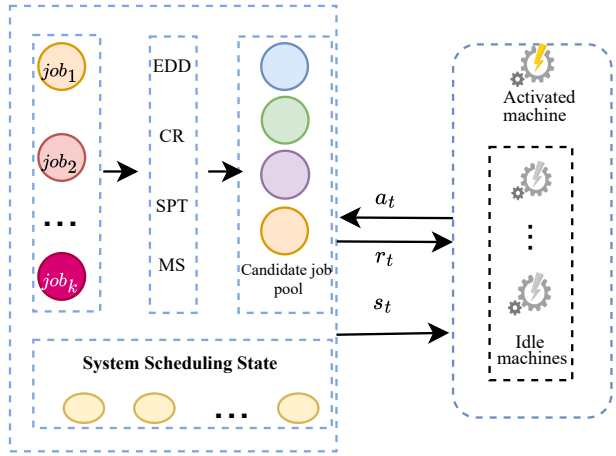


Fig. 1: Four dispatching rules (EDD, CR, SPT, MS) each recommend one candidate job. If fewer than four feasible jobs exist, masked dummy actions maintain a fixed action space. The state vector is constructed from features of these candidates and global system attributes.

D. Extrinsic and Intrinsic Reward

The proposed framework combines extrinsic rewards for scheduling objectives with intrinsic rewards to enhance learning under sparse feedback.

a) Extrinsic Reward: The primary objective of the scheduling task is to minimize the total tardiness of all jobs. At the end of each episode, the total tardiness is computed as

$$T_{\text{total}} = \sum_{i=1}^{n} \max(0, C_i - d_i), \tag{2}$$

where C_i and d_i denote the completion time and due date of job i, respectively. A negative terminal reward is then assigned to stabilize training:

$$r_T^{\text{ext}} = -\log(1 + T_{\text{total}}). \tag{3}$$

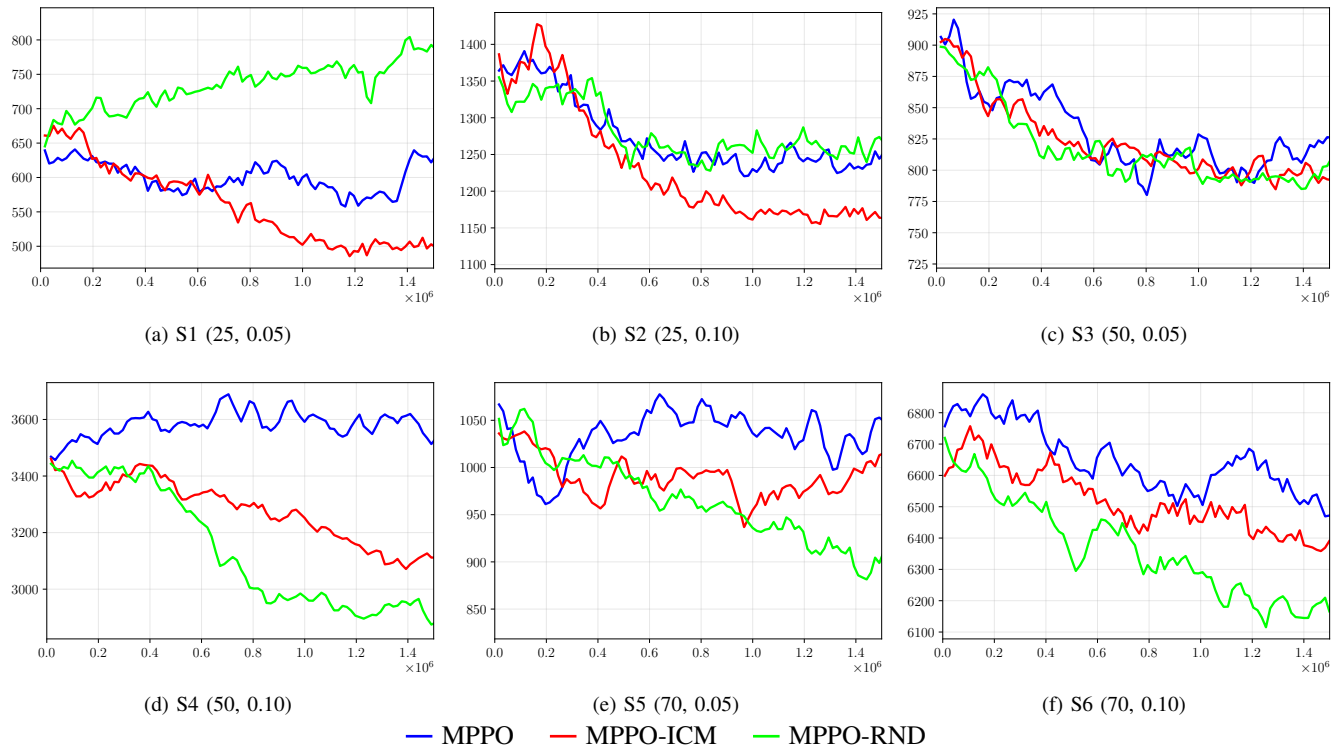
The logarithmic transformation stabilizes training by smoothing large tardiness values and reducing gradient variance. No external reward is given at intermediate steps, i.e., $r_t^{\text{ext}} = 0$ for $t < T$.

b) Intrinsic Reward: ICM: To encourage exploration under sparse extrinsic feedback, we employ the Intrinsic Curiosity Module (ICM) [13]. ICM consists of a forward model predicting the next-state representation $\hat{\phi}(s_{t+1})$ given (s_t, a_t), and an inverse model reconstructing the action from (s_t, s_{t+1}). The intrinsic reward is defined as the forward model's prediction error:

$$r_t^{\text{ICM}} = \|\hat{\phi}(s_{t+1}) - \phi(s_{t+1})\|_2^2, \tag{4}$$

where $\phi(\cdot)$ denotes a shared feature encoder. This reward motivates the agent to visit transitions that are difficult to predict. The forward model error can be decomposed into epistemic (reducible) and aleatoric (irreducible) components:

$$\mathbb{E}_{s'}\left[\|\hat{f}_\theta - \phi(s')\|^2\right] = \underbrace{\|\mathbb{E}_{s'}[\phi(s')] - \hat{f}_\theta\|^2}_{\text{Epistemic}} + \underbrace{\mathbb{V}_{s'}[\phi(s')]}_{\text{Aleatoric}}. \tag{5}$$



(a) S1 (25, 0.05) (b) S2 (25, 0.10) (c) S3 (50, 0.05)

(d) S4 (50, 0.10) (e) S5 (70, 0.05) (f) S6 (70, 0.10)

Fig. 2: Training results across six DFJSP scenarios (X: steps, Y: tardiness)

By emphasizing epistemic uncertainty, ICM facilitates structured exploration in predictable, low-load environments.

c) Intrinsic Reward: RND: As an alternative, Random Network Distillation (RND) [14] estimates state novelty via prediction error. A fixed random target network $g(\cdot)$ produces deterministic state embeddings, while a predictor network $\hat{g}_\psi(\cdot)$ is trained to approximate them. The intrinsic reward is

$$r_t^{\text{RND}} = \|\hat{g}_\psi(\phi(s_t)) - g(\phi(s_t))\|_2^2. \tag{6}$$

Under the empirical state distribution d^π, the expected reward satisfies

$$\mathbb{E}_{s\sim d^\pi}[r^{\text{RND}}(s)] = \mathbb{E}_{s\sim d^\pi}\left[\|g(\phi(s)) - \hat{g}_\psi(\phi(s))\|^2\right]. \tag{7}$$

For frequently visited states ($d^\pi(s)$ high), $\hat{g}_\psi$ fits well and $r^{\text{RND}}(s) \to 0$; for rare states, the prediction error remains large. Unlike ICM, RND's novelty estimation is independent of transition uncertainty $P(s'|s,a)$, making it robust to high-load stochastic environments where simple diversity-driven exploration suffices.

d) Total Reward: The agent's total reward combines extrinsic and intrinsic components:

$$r_t = r_t^{\text{ext}} + \beta r_t^{\text{int}}, \tag{8}$$

where r_t^{int} corresponds to either ICM or RND, and β balances exploration and exploitation.

III. Experiments

A. Experimental Setup

The proposed methods were evaluated in a DFJSP environment, where new jobs arrive according to a Poisson process with rate λ. Each job consists of 10–15 operations, each of which can be processed on one of several alternative machines. The environment is initialized with 10 available jobs, and the number of machines is fixed at 10 in all experiments. To examine scalability and robustness, six scenario combinations are considered: S1–S6 correspond to (Job number, λ) = (25, 0.05), (25, 0.10), (50, 0.05), (50, 0.10), (70, 0.05), and (70, 0.10). Each method is evaluated over 100 independent episodes with different random seeds to ensure statistical reliability.

The RL agent is implemented using MaskablePPO [15] from the stable-baselines3 [16]. Intrinsic motivation is provided by curiosity modules, including ICM and RND, from the RLLTE [17] and RLeXplore [18].

The key hyperparameters and network architecture are summarized in Table II.

Three methods are compared: **MPPO** (MaskablePPO baseline), **MPPO-ICM** (MPPO with Intrinsic Curiosity Module), and **MPPO-RND** (MPPO with Random Network Distillation). Performance is measured by the average total tardiness across 100 evaluation episodes per scenario.

B. Experimental Results

Table III reports the average total tardiness over 100 evaluation episodes for MPPO, MPPO-ICM, and MPPO-RND across

TABLE II: Key Hyperparameters and Network Architecture.

Category	Hyperparameter	Value
RL Algorithm		
	Discount Factor (γ)	0.995
	GAE Parameter (λ)	0.95 [a]
	Clipping Range (ϵ)	0.2
	PPO Epochs	10 [a]
	Minibatch Size	2048
	Value Loss Coefficient	0.5 [a]
	Entropy Coefficient	0.001
	Target KL Divergence	0.02
Network and Optimizer		
	Hidden Layer Dimensions	(128, 128, 64)
	Activation Function	LeakyReLU
	Optimizer	Adam [a]
	Learning Rate	3e-4
Training Setup		
	Total Timesteps	1.5e6
	On-policy Buffer Size (n_steps)	2048
	Number of Parallel Environments	8
	Observation Normalization	True
	Reward Normalization	True
	Intrinsic Reward Weight (β)	0.5

[a] Indicates default value from Stable-Baselines3.

TABLE III: Average total tardiness of the evaluated methods.

Method	S1	S2	S3	S4	S5	S6
MPPO	528.15	1177.91	727.18	3578.31	774.59	6430.17
MPPO-ICM	**465.46**	**1045.28**	**686.19**	3016.24	675.08	6012.54
MPPO-RND	571.22	1180.72	724.85	**2876.08**	**578.36**	**5705.83**

six DFJSP scenarios. MPPO-ICM consistently outperforms the baseline MPPO in all scenarios, while MPPO-RND shows improvements mainly in high-load scenarios with larger job counts or higher arrival rates (S4–S6) and performs comparably or slightly worse in low-load scenarios (S1–S3).

These trends align with the theoretical characteristics of the intrinsic reward mechanisms (Section II-D). As shown in Fig. 2, ICM, emphasizing epistemic uncertainty, converges faster in low-load, predictable environments, promoting structured exploration. RND, estimating state novelty independent of transition uncertainty, is more robust under high-load stochastic conditions, achieving lower final tardiness where diversity-driven exploration is beneficial. Overall, incorporating intrinsic motivation reduces total tardiness, with the relative effectiveness of ICM or RND depending on system load and scenario characteristics.

IV. Conclusion

This paper presents a curiosity-driven reinforcement learning framework to mitigate sample inefficiency under sparse rewards in DFJSP. By augmenting a MaskablePPO agent with intrinsic motivation mechanisms (ICM and RND), the framework promotes efficient exploration and yields policies that consistently reduce total tardiness compared to the baseline.

Theoretical analysis explains the observed performance differences: in low-load scenarios with largely deterministic transitions, ICM leverages prediction-error-based curiosity to drive structured exploration and generalize across sparse state spaces; in high-load stochastic scenarios, RND's fixed random network provides stable novelty signals, mitigating the impact of noisy predictions in ICM and enabling faster convergence toward exploitation. These results highlight the interplay between intrinsic reward design, system load, and transition dynamics.

Limitations include a constrained action space and centralized agent architecture, which may restrict policy discovery and scalability. Future work will explore adaptive intrinsic motivation, richer state/action representations, and multi-agent architectures for improved robustness and generalization.

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