Zhang, Ming, Lu, Yang ORCID:

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Dynamic Scheduling Method for Job-Shop Manufacturing Systems by Deep Reinforcement Learning with Proximal Policy Optimization

Ming Zhang, Yang Lu, Chao Liu and Yuchun Xu https://doi.org/10.3390/su14095177





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# 1. Summary

For increasingly complex modern manufacturing production systems, operational decision making encounters more challenges in terms of having **sustainable manufacturing to satisfy customers and markets' rapidly changing demands**. Nowadays, the efficiency of decision making could not be guaranteed nor meet the **dynamic scheduling requirement** in the job-shop manufacturing environment based on the traditional knowledge-based method. We propose using **AI-enhanced deep reinforcement learning methods** to tackle the dynamic scheduling problem in the **job-shop manufacturing system with unexpected machine failure**. The proximal policy optimization algorithm was used in the DRL framework to accelerate the learning process and improve performance.

# 2. Objectives



AI-enhanced Data-driven Method



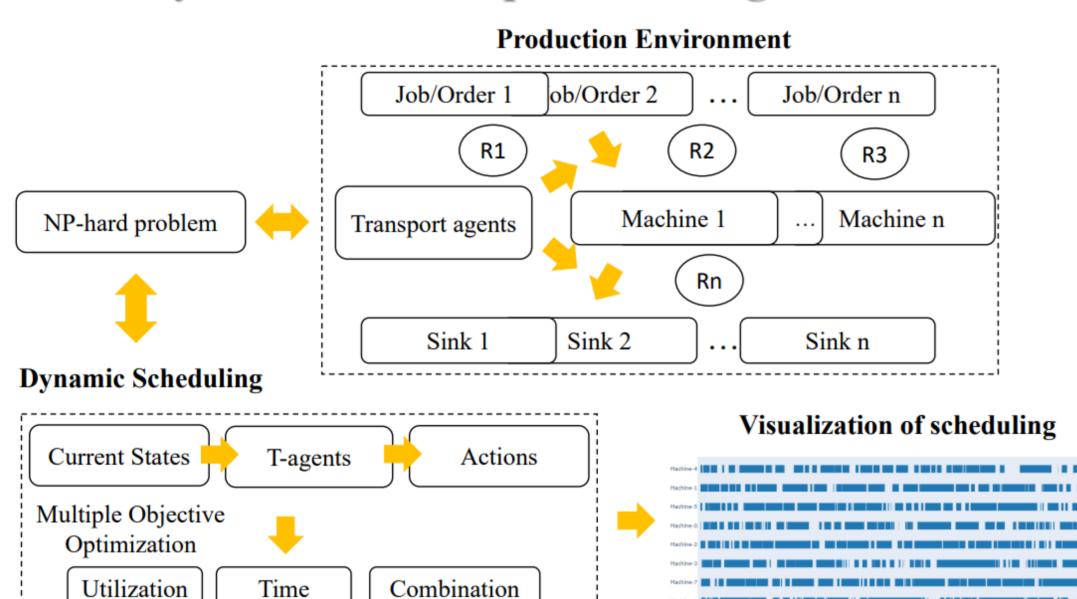
Sustainable Manufacturing



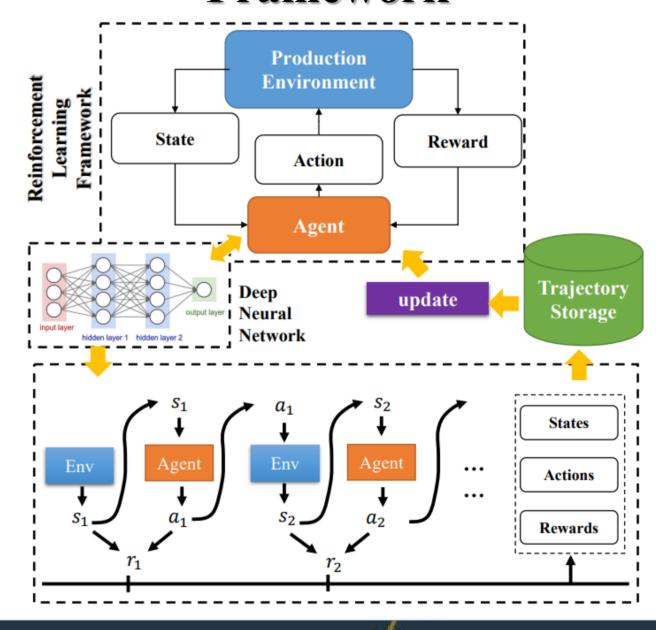
**Production High Efficiency** 

## 3. Method

### **Dynamic Job-Shop Scheduling Problem**



# Deep Reinforcement Learning Framework



# 4. Results

# Case Study D: Dispatcher Route Machine 3 Machine 4 Machine 5 Sink 2 Machine 6 Machine 7 Machine 8 Sink 3 Machine 6 Machine 7 Machine 8 Sink 3 PPO is the Best Figure 4 Learning process of different algorithms:

Figure 4. Learning process of different algorithms; (a) policy gradient (PG), (b) trust region policy optimization (TRPO), and (c) proximal policy optimization (PPO).

### **Sustainability Comparison**

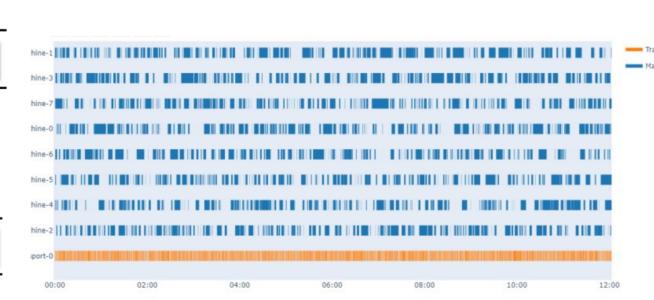


Figure 6. Gantt chart of operating state working with random policy

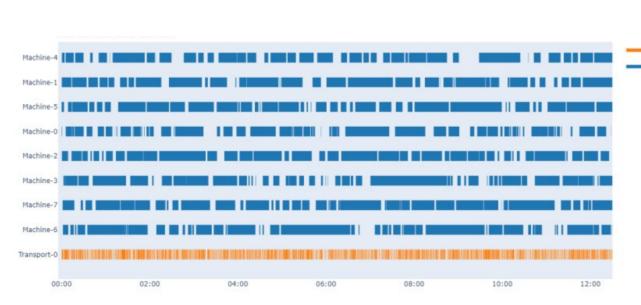


Figure 7. Gantt chart of operating state working with optimal policy trained by the PPO algorithm

### **Reward Function Comparison**

<b>Utilization:</b>
Cumzacioni

**PPO** 

### Waiting time:

 $R_{\omega-uti}(S_t, A_t) = \begin{cases} \omega_1 R_{uti}(S_t, A_t) & A_t \in A_{S \to M} \\ \omega_2 R_{uti}(S_t, A_t) & A_t \in A_{M \to S} \\ 0 & else \end{cases}$ 

 $R_{\omega-wt}(S_t, A_t) = \begin{cases} \omega_1 R_{wt}(S_t, A_t) & A_t \in A_{S \to M} \\ \omega_2 R_{wt}(S_t, A_t) & A_t \in A_{M \to S} \\ 0 & else \end{cases}$ 

Scenario 1

Table 5. Results for PPO dispatching approaches under different reward function in both production scenarios

	<i>U</i> (%)	WT(s)	α	
R <sub>const</sub>	$43.20 \pm 3.72$	$119.30 \pm 11.04$	$2.30 \pm 0.63$	
$R_{\omega-uti}$	$44.21 \pm 3.60$	$130.65 \pm 11.51$	$2.37 \pm 0.59$	
$R_{\omega-wt}$	$43.68 \pm 4.11$	$126.61 \pm 12.02$	$2.38 \pm 0.71$	
$R_{hybird}$	$43.35 \pm 3.67$	$124.53 \pm 19.15$	$2.32 \pm 0.62$	
PPO	Scenario 2			
	<i>U</i> (%)	WT(s)	α	
R <sub>const</sub>	$62.29 \pm 5.02$	$80.79 \pm 14.87$	$0.56 \pm 0.15$	
$R_{\omega-uti}$	$66.31 \pm 7.09$	$99.87 \pm 20.55$	$0.54 \pm 0.18$	
$R_{\omega-wt}$	$62.03 \pm 5.98$	$80.10 \pm 15.63$	$0.57 \pm 0.18$	
$R_{hybird}$	$62.75 \pm 6.99$	$80.56 \pm 17.12$	$0.54 \pm 0.19$	
	·	·		

**Multiple-objective:**  $R_{hybird}(S_t, A_t) = w_1 R_{uti} + w_2 R_{wt}$ 

Table 6. Results for different combination of parameters  $\omega_1$  and  $\omega_2$  under reword function  $R_{hybird}$  in production scenario 2.

	<i>u</i> (%)	WT(s)	α
$\omega_1 = 0.1,  \omega_2 = 0.9$	$61.89 \pm 5.81$	$80.99 \pm 16.14$	$0.57 \pm 0.16$
$\omega_1 = 0.25$ , $\omega_2 = 0.75$	$62.30 \pm 6.08$	$80.35 \pm 14.69$	$0.56 \pm 0.17$
$\omega_1 = 0.5$ , $\omega_2 = 0.5$	$62.75 \pm 6.99$	$80.56 \pm 17.12$	$0.54 \pm 0.19$
$\omega_1 = 0.75$ , $\omega_2 = 0.25$	$68.46 \pm 7.02$	$106.22 \pm 19.30$	$0.48 \pm 0.16$
$\omega_1=0.9,\omega_2=0.1$	$69.79 \pm 7.16$	$104.88 \pm 20.29$	$0.44 \pm 0.16$
	·	·	·

## 5. Conclusion

The deep reinforcement learning framework with the PPO algorithm has been approved as a suitable solution to the dynamic scheduling problems in the manufacturing environment. This research is still in the initial phase. However, it shows the powerful potential of data-driven AI-based methods to significantly enhance the manufacturing process.

Dr Ming Zhang m.zhang21@aston.ac.uk Prof. Yuchun Xu

v.xu16@aston.ac.uk

Dr Chao Liu liuc16@aston.ac.uk