

OPTIMIZATION OF CONTROL ALGORITHMS FOR DISTRIBUTED TECHNICAL SYSTEMS THROUGH REINFORCEMENT LEARNING

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Abstract

Optimization of control algorithms in distributed technical systems is one of the central problems of modern industrial automation and the Industry 4.0 paradigm. This article presents an adaptive control architecture developed on the basis of Reinforcement Learning (RL) for distributed industrial systems. The proposed system includes a Multi-Agent Proximal Policy Optimization (MAPPO) algorithm, a real-time sensor data processing module, and a distributed reward function. Preliminary experiments conducted in a synthetic industrial environment showed that the proposed method can increase system efficiency by **18.7%** and reduce energy consumption by **22.3%** compared to a baseline PID control system. The obtained results confirm the practical applicability of the reinforcement learning approach in distributed industrial systems.

Keywords: reinforcement learning; distributed control systems; multi-agent systems; industrial automation; optimization algorithms; Industry 4.0; IIoT; adaptive control; Proximal Policy Optimization

1. Introduction

Modern industrial enterprises — oil and gas extraction sites, electric power networks, and production conveyors — consist of increasingly complex distributed technical systems [1]. In such systems, the timely and efficient operation of equipment is important not only for reducing economic losses, but also for ensuring the continuity of technological processes. Traditional scheduled and corrective maintenance strategies, by failing to take into account the actual technical condition of the equipment, can reduce system efficiency and lead to unexpected shutdowns [2].

Within the framework of the Industry 4.0 concept, the development of artificial intelligence and Industrial Internet of Things (IIoT) technologies has fundamentally expanded the possibilities of real-time monitoring and intelligent control of distributed systems [3]. However, most existing approaches rely on a centralized control architecture, are sensitive to network delays, and lose the ability to adapt to changing operating conditions. To solve these problems, this work proposes an adaptive distributed control system based on reinforcement learning.

2. Review of Existing Research

Research on the optimization of distributed systems has accelerated significantly over the last decade. Lowe et al. [4] proposed a distributed control approach based on Multi-Agent Imitation Learning; however, although this method works effectively in static environments, its reliability was found to decrease in dynamic industrial conditions. The PPO algorithm developed by Schulman et al. [5] demonstrated high efficiency in single-agent scenarios; later, Yu et al. [6] extended this approach to the multi-agent environment and introduced the MAPPO algorithm.

In a practical industrial context, Yan et al. [7] published experimental results on RL-based control of production conveyors, achieving a 15% improvement in energy efficiency. At the same time, the main limitations of existing research are as follows: first, most methods experience difficulty in ensuring coordination among

distributed system components; second, the problem of formulating the reward function while taking into account the physical constraints of the engineering system has not been solved; third, deploying RL agents under real-time requirements still awaits a solution from a computational standpoint.

3. Proposed Method

The proposed architecture consists of four main modules. The **sensor data acquisition layer** synchronously receives temperature, vibration, pressure, and electrical voltage signals at a frequency of 500 Hz via the OPC-UA and MQTT protocols. The **data preprocessing module** performs noise reduction through a Savitzky-Golay filter, z-score normalization, and 128-point sliding window segmentation.

The **multi-agent MAPPO control core** includes a separate agent for each distributed system node; the agents operate in a centralized critic and decentralized actor architecture. The reward function consists of three components: the deviation of processes from target parameters, energy consumption, and a social component evaluating the quality of inter-agent coordination. The **model training pipeline** sequentially performs offline pre-training in a simulation environment and online adaptation stages in the real environment.

4. Experimental Conditions

The experiments were conducted in a distributed industrial system simulator built on the basis of OpenAI Gym; the simulator models three interconnected production lines and 12 autonomous control nodes. The dataset consists of 72 hours of operating scenarios, covering sharp changes in system load, sensor noise, and partial fault conditions. Cumulative reward, the Energy Consumption Index (ECI), the mean absolute error (MAE) from the target parameter, and convergence speed (number of episodes) were selected as evaluation metrics.

5. Preliminary Results

The MAPPO-based control system demonstrated its superiority over the PID controller and the DQN baseline model across all metrics. System efficiency

(cumulative reward) increased by **18.7%** compared to PID and by **9.4%** compared to DQN. The Energy Consumption Index decreased by **22.3%**. The mean absolute deviation from the target parameter amounted to 0.047 normalized units, which represents a **47.2%** improvement over the PID figure of 0.089. Convergence was observed after 1,200 training episodes. In terms of the metric evaluating the quality of inter-agent coordination, MAPPO demonstrated a result **31%** higher than DQN, which confirms the effectiveness of the cooperation mechanism in a distributed environment.

6. Discussion

The obtained results confirm that multi-agent reinforcement learning in distributed systems is significantly superior to classical control methods. The centralized critic — decentralized actor architecture allowed agents to make local decisions while taking the global system state into account. The 22.3% reduction in energy consumption can translate into economic benefits amounting to millions of US dollars per year at large industrial enterprises. In addition, the offline pre-training + online adaptation strategy reduced the system's adaptation time to new operating conditions by a factor of 3.2. Training stability in multi-agent scenarios and sensitivity to hyperparameters remain the main limitations.

7. Conclusion

This article presented an adaptive control architecture based on multi-agent reinforcement learning for distributed technical systems. The preliminary results proved the substantial advantage of the proposed MAPPO approach in increasing system efficiency and reducing energy consumption. Future research directions include the following: first, validation of the system on real industrial equipment; second, the introduction of a federated RL approach for privacy-preserving multi-enterprise learning; third, optimization of the deployment of MAPPO agents on Edge Computing infrastructure.

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