Dissertation Defense

REINFORCEMENT LEARNING-BASED OPTIMIZATION FOR COMPLEX SCHEDULING PROBLEMS: ADDITIVE MANUFACTURING AND DATA CENTERS

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Dissertation Abstract

Efficient scheduling is essential for improving system performance, resource utilization, and operational reliability in modern industrial systems. However, many real-world scheduling problems involve complex constraints, heterogeneous resources, and stochastic outcomes that are difficult to address using traditional optimization or heuristic approaches. This dissertation develops a Reinforcement Learning (RL)-based scheduling framework designed to solve complex, resource-constrained, and uncertainty-driven scheduling problems. The framework integrates optimization modeling with RL to enable adaptive decision-making in dynamic industrial environments. The first study investigates scheduling in multi-laser metal additive manufacturing (AM), where multiple independently driven lasers must coordinate their scanning operations to fabricate large-scale components efficiently while preserving product quality. A multi-laser scan assignment and scheduling problem is formulated to minimize total makespan while enforcing manufacturing quality constraints. Two classes of quality-driven constraints are modeled: Heat-Affected Zone (HAZ) avoidance to reduce thermal interference between lasers, and user-specified single-laser scanning regions for complex geometric features. To solve this constrained scheduling problem, a Deep Reinforcement Learning (DRL) framework is developed that learns adaptive scan assignment and sequencing policies. The proposed approach enables flexible integration of process constraints while maintaining computational scalability as the number of lasers increases. Experimental studies demonstrate that the DRL-based scheduler improves coordination among multiple lasers and achieves shorter makespans compared with conventional heuristic scheduling strategies. The second study extends the proposed RL framework to scheduling in System Integration Validation Testing (SIVT) during the New Product Introduction (NPI) process for large-scale data center systems. In this environment, validation consists of numerous hardware and software tests with heterogeneous resource requirements, including automated tests requiring hosts and manual tests requiring both hosts and operators. In addition, test outcomes are uncertain, leading to repeated executions due to failures. A custom RL environment is developed to capture these operational characteristics, including hybrid resource constraints and stochastic test failures with limited retry attempts. Using the Proximal Policy Optimization (PPO) algorithm, the RL agent learns resource allocation and test sequencing policies that

minimize the overall validation completion time. Simulation experiments show that the proposed framework effectively adapts to varying resource configurations and failure probabilities, demonstrating strong robustness under uncertainty. Together, these studies establish a unified RL-based scheduling methodology capable of addressing deterministic and stochastic scheduling problems across diverse industrial domains. This dissertation develops a modeling framework that incorporates complex operational and quality-related constraints into RL–based scheduling. It further proposes a scalable RL architecture capable of addressing large-scale scheduling problems with heterogeneous resources and dynamic system conditions. Finally, extensive experimental studies demonstrate the effectiveness and adaptability of the proposed approach in both manufacturing systems and data center validation environments. These contributions provide a foundation for applying RL to next-generation intelligent scheduling systems in complex industrial environments.