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Flexible Simulation Environment for AI-Driven Production Optimization*

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Abstract

Modern manufacturing increasingly relies on artificial intelligence to optimize complex production lines where historically, performance tuning was expertly engineered and incremental. AI methods ranging from evolutionary algorithms to reinforcement learning require large volumes of consistent, high-fidelity data[2, 9] to learn policies that balance throughput, scrap rates, cycle time, and energy use. In real plants, collecting such data is slow, disruptive, and labor-intensive. A flexible, high-confidence simulation system closes this gap by generating rich, reproducible datasets at scale[1, 7], enabling rapid exploration of control strategies and layouts. Even small improvements in transfer times, buffer sizing, scheduling, or quality yields compound over time, resulting in noticeable gains in OEE[1] [1, 7] and cost per unit.

Prior AI-based approaches to production optimization span evolutionary metaheuristics and deep reinforcement learning for dispatching and sequencing. Hybrid schemes couple DRL with multi-objective evolutionary search to balance throughput, tardiness, and energy. Simulation-based optimization has also targeted material supply and buffer sizing using shopfloor telemetry[2], delivering improvements in cycle time, and OEE[2–4, 6–9].

We present a general-purpose production-line simulator designed specifically for AI-based optimization workflows. The system is highly configurable along two dimensions: (1) PLC-level settings that determine control flow, interlocks, and state

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[1]Overall Equipment Effectiveness
[2]Real-time data from the production floor

transitions, and (2) the physical and logical layout, including stations, buffers, conveyors, parallel branches, and routing rules. This dual-surface configuration enables users to optimize a single line by tuning PLC parameters (e.g., timers, changeover rules) and also to perform meta-optimization across alternative layouts[2, 5] (e.g., changing station counts, buffer placements, parallelization, and carrier routing schemes). Configuration is declarative, allowing rapid iteration, automated search, and A/B testing[5] of designs without costly re-modeling.

Despite broad flexibility, the simulator remains efficient through a discrete-event architecture that computes only the necessary state changes. Rather than advancing time in uniform steps, the engine schedules and processes events such as the arrival or departure of workpiece carriers, resource acquisitions/releases, and machine cycle completions. This event-driven approach eliminates redundant time steps and focuses computation on the causal transitions that shape throughput and queues. The simulation maintains priority queues for events, resolves resource contention, and models machine error rates, maintenance requirements, and periodic service tasks (e.g., refills and calibrations). As a result, large scenario batches can be executed quickly, supporting AI training loops, sensitivity analyzes, and robust evaluations under uncertainty.

For industry to adopt AI-driven optimizations, high-fidelity and explainable methods are essential for cost and risk mitigation. By coupling configuration flexibility with an efficient event engine, the simulator offers a practical bridge between AI-based optimization and real factory operations. It enables faster, safer, and more cost-effective optimization across diverse lines, making continuous improvement repeatable, explainable, and data driven.

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