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MAINTENANCE DECISION-MAKING SUPPORTED BY A MULTI-FIDELITY SIMULATION OPTIMIZATION FRAMEWORK

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Abstract

Digital twin technology is becoming more prevalent in manufacturing. Simulation optimization is often used as the main component in digital twin. However, if simulation optimization is to be used to make real-time decisions, there is a need to improve its efficiency. We describe a multi-fidelity simulation optimization framework to support a real-time repair scheduling problem on a production line. When several machines are out of action on a production line, it is not obvious how to choose the order in which they should be repaired and the optimal choice will depend on the current state of the line. Simulation can be used to estimate the throughput of the line in the short term future for different repair orders and a given system state, but the speed at which results are required necessitates the development of an efficient optimization framework that minimizes the number of replications made of the complex simulation model.

1 INTRODUCTION

Unscheduled disruption to production lines can occur and when more than one machine on the line has malfunctioned, a decision often needs to be made about the order in which they should be repaired. Optimizing the repair order can improve the production throughput and simulation is often the most effective tool to assess the effects of a repair policy on production throughput. We use a multi-fidelity simulation optimization approach to find a good repair policy for maximizing the system throughput, given the current state of the system, in the subsequent three hours of system time. This draws on the method in (Cao et al. 2021), but applies it to a more complex situation. A key requirement of the optimization is that it can return results quickly (i.e., within minutes) to enable real-time decision-making.

2 CASE STUDY OF A PRODUCTION LINE

We consider a manufacturing production line consisting of 30 workstations, which are a mix of single and parallel machines (See the illustration in Figure 1). The high fidelity model used to describe the system is a Discrete Event Simulation (DES) model built with Simpy package (SimPy 2020). We use empirical distribution functions (EDF) to model the key repair distributions 'time between failure' (TBF) and 'time to repair' (TTR), where the EDFs are based on historical data from the production line. As we simulate the performance from a given system state, a hot start is used so that the simulation can start from any given system state.

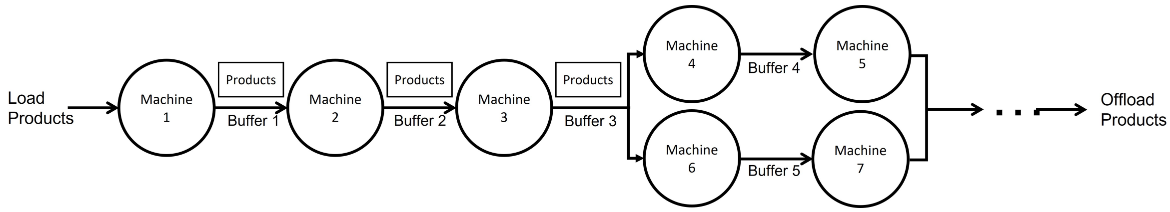

Figure 1: Illustration of a production line.

The optimization problem we solve is one of identifying the best repair policy to follow in order to maximize throughput over the following three hours. Based on Panwalkar and Iskander (1977), we consider ten repair policies: FIFO: earliest breakdown first; LIFO: latest breakdown first; SRT: shortest repair time first; LRT: longest repair time first; FOR: fewest operations remaining first so that machines nearer the end of the line have the priority; MOR: most operations remaining first so that machines nearer the start of the line have the priority; NOSQ: prioritize the machine whose next operation has the shortest queue; COLQ: current operation with longest queue first; AP: adjacent processes first so that adjacent breakdowns have the priority; NAP: non-adjacent processes first.

A metamodel is a surrogate model of the simulation in a fixed feasible area R^d built from noisy observations $Y = [y_1, y_2, ..., y_N]^T$ at design points $X = [x_1^T, x_2^T, ..., x_N^T]$ (Barton 2020). If all of the system parameters (i.e. the status of every buffer and machine) were included in the metamodel, the state space would be very large and a significant number of replications would be needed in order to fit the metamodel. As a result, we consider a simplification where we split the line into four sections and use as our input variables the status of the line in each of these four sections. This leaves us with five variables in our metamodel: the total buffer content in each of the four sections of the line; the number of parallel machines broken down in each of the four sections; the number of single machines broken down in each of the four sections; the adjacency of breakdowns; and the repair policy being implemented.

Having simplified the space, several different system states are described by just one metamodel input. In order to explore the difference between scenarios with the same set of metamodel inputs, we investigated extreme scenarios (e.g. same buffer content in each section but work-in-progress clustered at the start or end of the section) to determine whether the throughput was significantly different. After simulating 100 replications for each scenario, over half (43/81) of the scenarios are found to have no statistically significant difference and consequently we believe that the simplification is valid. Sequential sampling is used to guide the experimental design.

3 CONCLUSIONS AND FUTURE WORK

We apply a multi-fidelity simulation optimization algorithm to the problem of identifying an appropriate repair policy on a production line. The work is useful in situation where the digital twin simulation model is computationally expensive to run while real-time decisions are needed. Current work is focused on fitting a neural network metamodel to the DES output.

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