Rescheduling and co-simulation of a multi-period multi-model assembly line with material availability restrictions *

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This paper presents a real-time optimization and co-simulation framework for manufacturing environments. The aim is to handle disruption events related with component availabilities and machine breakdowns. This framework is part of the DISRUPT ecosystem [1] and has been installed and tested at two industrial users, a large consumer electronics and white appliances manufacturer and a major European car manufacturer. This paper reports preliminary results obtained from the automotive production plant.

Car production involves thousands of components that come from a large network of suppliers. In the examined use case, a make-to-order policy is followed, while safety stock levels for critical components are kept as low as possible. In this environment, any disruption in the scheduled arrivals and availability of components may cause production delays with significant financial impact. The technology developed within DISRUPT enables real-time monitoring of the supply chain and the production processes via cyber-physical systems (CPS) and complex event processing (CEP) tools. These systems generate events that may trigger simulation and optimization tools in an iterative fashion. The aim of simulation is to evaluate the impact of events on various KPIs, while based on this information optimization seeks to react and re-schedule accordingly the production plan.

Automotive manufacturing typically consists of a paced assembly line with many process steps, where multiple car models are sequenced for production. A car model enters the assembly line once all necessary components have arrived at the production floor, together with the main body that has exited the paint shop. Given a master production schedule, the material requirements are determined and the necessary replenishment orders for all components are issued. On this basis, a dock schedule is generated that provides details regarding the quantities, the arrival times and assigned dock station for each truck. To that end, a detailed production plan is generated that describes the exact sequence of production orders per day for a specific planning horizon (typically four months). In practice, this detailed production plan is subject to change on a weekly basis due to the occurrence of unexpected events (e.g. material

*Research supported by the European Commission under the project DISRUPT: Decentralized architectures for optimized operations via virtualized processes and manufacturing ecosystem collaboration (Horizon 2020, 723541)

[1]EU project DISRUPT (http://www.disrupt-project.eu/)

unavailabilities, machine break-downs and quality problems).

The associated production scheduling problem can be depicted as a multi-period multi-product machine scheduling problem with component availability restrictions. In particular, the assembly line is modeled as a single machine. All production orders have the same processing time (independent of the type of car model), and the resulting scheduling problem is simply to determine the sequence of production orders to execute per day over a planning horizon of multiple weeks. However, a production order can be scheduled only if all components are available. During each day, trucks deliver components to the docks of the plant every hour. Although each truck is dedicated to deliver a specific family of components (e.g. seats), the delivered quantities and frequencies fluctuate, and this further complicates the scheduling problem. This results to sparse feasible component availability windows, which may change completely because of disruption events in the supply chain. It is also worth to highlight that even small delays may propagate significant changes in the production schedule.

Component unavailabilities due to delayed deliveries or due to quality issues in the paint shop can be handled by re-scheduling the existing plan so as to postpone the affected production orders. There are two rescheduling options, i.e., changes in the daily execution sequence and swapping of production orders between two days. Each rescheduling option comes with specific labor cost. We also assume that there is no cost to make changes in the master schedule after one week and that all logistic issues can be fully resolved and all components will be available after 5 days. To that end, the aim of re-scheduling is to minimize the cost and the number of changes in the existing plan.

There is a vast literature on real time scheduling problems and various methodologies have been proposed for similar type of problems, including heuristic, mathematical programming, and constraint programming methods. For the examined use case, we resort to a meta-heuristic approach for solving the scheduling problem due to the wide length of the planning horizon and the requirement for very short reaction times to disruption events. Our approach is based on tabu search and it is capable of producing near optimal solutions in relatively short computational times. It is equipped with tailored-made neighborhood structures and adaptive memories that are used to guide the search to promising regions of the solution space. Also specialized data structures are employed to accelerate the process of identifying feasible solutions in terms of material availability.

From the algorithmic viewpoint, the rescheduling process consists of two main phases. During the first phase, we seek to identify the time windows where material stock-outs occur. Next, we try to resolve all infeasibilities by re-arranging orders so that an optimization objective is minimized. In this work a hierarchical objective function is adopted. The primary objective is to minimize rescheduling cost, and among schedules with the same re-scheduling cost, the secondary objective is to maximize “robustness”. Schedule robustness can be seen as time-buffer and it is calculated as the time difference between the start time of a production order and the last replenishment time of critical components that are prone to stock-outs The idea behind this metric is to anticipate and absorb potential late deliveries. For the calculation of the scheduling robustness, the optimization is assisted by simulation in order to identify these critical components. In the proposed optimization and co-simulation scheme whenever a new production schedule is generated, simulation is triggered to evaluate the schedule. Among other KPIs, simulation can identify the components that are more prone to cause production delays. On return, the optimization algorithm is using this information (as described above) so as to introduce time-buffers and improve the overall robustness of the schedule.