Closed-loop Rescheduling using Deep Reinforcement Learning

Jorge A. Palombarini[1] and Ernesto C. Martínez[2]

[1]Centro de Investigaciones y Transferencia Villa María (CIT-VM, CONICET-UNVM)
[1]Depto. Ing. en Sistemas de Información, (UTN FRVM)
jpalombarini@frvm.utn.edu.ar

[2]Instituto de Desarrollo y Diseño (INGAR, CONICET-UTN)
ecmarti@santafe-conicet.gov.ar

Modern socio-technical manufacturing environments are characterized by high demand variability, product complexity and routing flexibility in the manufacturing processes, as well as by higher levels of decision-making autonomy at the shop-floor. In such environments, disruptions show up as a set of unplanned events (e.g. machine breakdowns, rush orders and quality problems) that require reactive rescheduling control. To ensure the real autonomy of the shop-floor, the personnel are empowered with enough autonomy to make rescheduling decisions to respond timely to disruptive events. Closed-loop rescheduling is thus appealing to handle unforeseen events by increasing the autonomy and responsiveness of the shop floor which are associated with timely and appropriate schedule repair actions taken in response to the mentioned events. The vast majority of the scheduling research does not explicitly consider execution issues such as uncertainty, and implicitly assumes that the global schedule will be executed exactly as it emerges from the algorithm that generates it. So, the rescheduling problems are modelled and solved based on well-defined, simplified and structured mathematical definitions. Such assumptions provide a relatively narrow perspective when compared to the complexity of industrial scheduling practice where reschedulers must respond to disruptions in real time and cannot solve from scratch a rescheduling problem every time an unforeseen event occurs. Therefore, it is essential to pursue a paradigm shift from off-line planning systems to on-line and closed-loop control systems, which take advantage of the ability to act interactively with the user to counteract the effects of unforeseen events under different schedule repair goals. In this work, a novel approach for generating rescheduling knowledge which can be used in real-time for handling unforeseen events without extra deliberation is presented. For generating such control knowledge, the rescheduling task is modelled and solved as a closed-loop control problem by resorting to the integration of a schedule state simulator with a rescheduling agent that can learn successful schedule repairing policies directly from a variety of simulated transitions between schedule states, using as input readily available schedule color-rich Gantt chart images, and negligible prior knowledge. The generated knowledge is stored in a deep *Q*-network, which can be used as a computational tool in a closed-loop rescheduling control way that select repair actions to make progress towards a goal schedule state, without requiring to compute the rescheduling problem solution every time a disruptive event occurs and safely generalize control knowledge to unseen schedule states