5 Concluding Remarks

A novel strategy for simulation-based learning of a rule-based policy has been presented, which deals with automated repair in real time schedules using reinforcement learning in the Soar cognitive architecture. The policy generates a sequence of local repair operators to achieve rescheduling goals in order to handle abnormal and unplanned events such as inserting an arriving order with minimum tardiness based on a symbolic first order representation of schedule states using repair operators. The proposal efficiently use and represent large bodies of symbolic knowledge, as it dynamically combines available knowledge for decision-making in the form of production rules with learning mechanisms, and it can compile the rescheduling problem solving into production rules, so that the schedule repair process is replaced by rule-driven decision making which can be used reactively in real-time in a straightforward way. Finally, relying on an appropriate and well-designed set of template rules, the approach enables the automatic generation through reinforcement learning and chunking of rescheduling heuristics that can be naturally understood by an end-user.

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