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Evaluating the Robustness of Production Schedules using Discrete-Event Simulation

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Abstract: Complex stochastic job-shop scheduling problems can be handled by simulation-based optimization (SBO), combining the optimization capabilities of meta-heuristics with the system representativeness of simulation models. In order to explore the potential of coupling optimization and simulation techniques in different job shop scheduling scenarios, this paper presents some of the ideas on an ongoing research project developing an SBO strategy coupling genetic algorithm and discrete-event simulation. Furthermore, this paper describes an approach to aid in the analysis of computed schedule feasibility subject to stochastic behavior, which is the case for most of the real world industries. One of the research goals is to provide an efficient and effective way to evaluate schedule robustness and to find robust schedules. The research may significantly contribute to businesses where scheduling changes are expensive, like in airline and train companies and automakers industries and suppliers.

Keywords: Schedule robustness; Production planning and control under uncertainty; Job and activity scheduling

1. INTRODUCTION

The specification of efficient production schedules is important for job shop manufacturing systems execution. Each order has to be assigned to an available machine so that specific performance measurements are improved. However, the increasing customization of products requires that production handles higher numbers of product variants along with decreasing lot sizes. Furthermore, to ensure process quality and speed, several specialized machines are employed. Hence, job shop manufacturing systems become more complex and the efficient management of these systems requires reliable and robust scheduling methods. In general, the computation of schedules employs optimization techniques, such as mixed-integer programming (Mula et al., 2010) but do not consider schedule stability or robustness.

Despite the increasing power of modern solvers, most real manufacturing systems are still too complex to be properly represented, modeled and solved without ample simplifications (they belong to the class of NP-hard optimization problems). As a consequence, the optimal solution often cannot be computed or requires long computation times. Therefore, frequently heuristic methods are applied. These methods cannot guarantee optimality but are often able to generate near-optimal solutions in relatively short computation times (Papadimitriou, 2003). One of the simplest heuristic scheduling approaches is the use of dispatching rules, assigning a specific priority value to each job (or order) in the queue of a machine according to some predefined criteria, such as the remaining time until its due date (Pickardt and Branke, 2012; Rajendran and Holthaus, 1999). Whenever a suitable machine is available, the job with the highest priority is chosen for the next operation. Due to the low implementation effort, dispatching rules are often used. A more sophisticated approach, which offers more flexibility, is the use of meta-heuristics, such as genetic algorithms. Genetic algorithms are able to compute solutions also for larger instances of combinatorial problems than exact optimization methods. However, they also feature limitations, such as the dependence on the choice of several parameters and the possibility to converge towards local extrema (Jungwattanakit et al., 2008). Moreover, both, exact optimization methods as well as meta-heuristics are not able to deal with two particular characteristics of production systems: dynamics and randomness (stochasticity), which can greatly compromise the initial production schedule.

During production, it is well known that random events occur affecting the adherence to a production schedule. Indeed, production systems can be regarded as dynamic systems that are subject to internal as well as external dynamic and unexpected factors, such as: (i) changes and delays in raw/component materials arrival from suppliers; (ii) unacceptable quality for raw/component materials from suppliers or during production, leading to reprocessing, reworks and reordering, and consequently to delays; (iii) unexpected production resources (machines, tools, castings etc.) failures, which require stops for maintenance and repair; (iv) workers absenteeism; (v) need for extra cleaning of production resources and other unexpected setup activities (Vieira et al., 2003; Vieira et al., 2009a; Vieira et al., 2009b; Scholz-Reiter et al., 2002).

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Because of the high degree of interdependencies between processes within production systems, disturbances can accumulate, so that even small changes of system parameters can have a big impact on the performance of the system (Prabhu and Duffie, 1999). For example, an increased production time in one machine can lead to delays that might impose delays in all subsequent production steps and a previously computed schedule might be inefficient or even infeasible in the new situation. In a broader sense, changes in a production schedule within and car assembly line can affect dozens if its suppliers.

In addition, manufacturing systems feature several stochastic characteristics. Processing and setup times can be regarded as stochastic times. For instance, these times depend on the capability level of a worker, the specific surface of a work piece or the wear of a used tool. Therefore, some variables of the scheduling problem cannot be regarded as completely deterministic and known values but have to be expressed in terms of a probability function. In literature, it is suggested that complex stochastic problems can be solved by simulation-based optimization (SBO), combining the power of meta-heuristics for optimization with the advantages of simulation models (Ge et al., 2014; Lin and Chen, 2015). In order to describe the potential of coupling optimization and simulation techniques in the case of job shop scheduling, this paper proposes a hybrid approach combining a genetic algorithm and discrete-event simulation. The genetic algorithm is applied to compute a nearly optimized production schedule. However, since production systems are dynamical systems, computed schedules are often not feasible if they are vulnerable to delays (or cancelations), for example regarding processing times or setup times, and in particular large delays, for instance caused by machine failures. In order to determine the feasibility, and later on, robustness, of a schedule, this paper applies discrete-event simulation. As an initial approach, the difference between the theoretical (schedule based) maximum completion time (Cmax) of a schedule and the mean Cmax based on simulation is regarded as an indicator for schedule feasibility (or robustness). Therefore, one can see this as a first approach to evaluate robustness of computed production schedules in complex stochastic job-shops. In case of a large difference between these values, other possible schedules generated by the genetic algorithm are simulated in order to find a more robust and thus feasible schedule. Industrial companies can clearly benefit from this approach since they can plan the completion dates of their products more realistically. This better planning impacts positively on several other planning processes, such as the planning of production capacities, the arrangement of transport processes or the agreement on due dates with customers.

The remainder of this paper is structured as follows: The next section presents a brief literature review regarding scheduling, simulation and robustness. Subsequently, a hybrid approach combining a genetic algorithm and discrete-event simulation is applied to two simple use cases of job shop scheduling. The paper sums up with a conclusion and an outlook on future research directions.

2. LITERATURE REVIEW

The complexity of most of real-world production systems is related with their dynamic and stochastic nature as well as to a multitude of internal and external interactions. On the sequence, a brief literature review regarding production scheduling is presented: first, the definition of robustness is explored; then, different approaches for simulation-based optimization are presented.

2.1 Robustness of production schedules

Being able to develop a schedule that performs well under real world scenarios is definitely still a challenge. Schedule robustness (or a robust schedule) has been defined by many researchers in different areas, but they all lean towards similar ideas. For instance, robustness has been defined as the capability to handle small delays (Andersson, 2014), to resist to imprecision (Salido et al., 2008), to tolerate a certain degree of uncertainty (Policella, 2005) or to cope with unexpected troubles without significant modifications (Takeuchi and Tomii, 2005). More specifically, a robust schedule is the one which minimizes the impact of delays and disruptions once a schedule gets disrupted or minimizes expected schedule costs (Chiraphadhanakul and Barnhart, 2011; Hadianti et al., 2013). Robustness can be characterized as a situation when performance is rather insensitive to the data uncertainties (Billaut et al., 2008). In order to quantify robustness, Vieira et al. (2009a, 2009b) have considered simulation-based approaches to model and estimate robustness in real world scenarios and consequently proposed a robustness index. Finally, it is important to remark that robust scheduling is not necessarily optimal in planning, but performs well in operations (Klabjan et al., 2001).

2.2 Simulation-based optimization in production scheduling

Historically, one of the most suitable ways to derive experience-based solutions to deal with real-world complex systems is through their modelling and simulation (Longo, 2010). Simulation-based techniques can be used either to develop or to evaluate complex systems. Aspects like the physical configuration or operational rules of a system can be considered. Its applications have grown in all areas, assisting managers in the decision making process and enabling a better understanding of processes in complex systems (O'Kane et al., 2000). Thus, simulation models can be used both as an analytical tool for predicting the effect of changes to existing systems and as a design tool to predict the performance of new systems under varying circumstances. According to O'Kane et al. (2000), simulation models have become one of the most popular techniques used for the analysis of complex industrial systems with the greatest potential for applications on the operational level. In the simulation process, the model represents the key characteristics, behaviors and functions of the selected physical or abstract system. Simulation models address 'what if' questions: What will likely happen over time and at which specific places if a particular design and/or operating policy are implemented? Banks et al. (2000) state that a simulation model usually takes the form of a set of assumptions concerning the operation of the system. These assumptions