Challenges of Stochastic Project Scheduling in Manual Manufacturing: A Hybrid Simulation-Based Scheduling Approach

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***Abstract*—Solving Stochastic Resource-Constrained Multi-Project Scheduling Problems (SRCMPSP) is an upcoming topic. Numerous variants, smaller batch sizes and shorter product life cycles lead to more uncertainty. In Production Planning and Control (PPC), stochastic scheduling approaches are coming into focus. The schedule thus is determined during production without following a baseline schedule. In our research project Hybrid PPC, we develop robust heuristics for stochastic project scheduling. The purpose of the approach is a central, simulation-based generation of a decentralized control system. As part of the research, we investigate benchmarking of SRCMPSP, evaluation strategies, as well as heuristic and solution robustness.**

Keywords—stochastic processes; scheduling algorithms; benchmark testing.

I. INTRODUCTION

Mechanical and systems engineering is increasingly becoming a project business (large number of variants, batch size one) [1]. The main driver is the increasing individualization. This is accompanied by more fuzzy data (e.g., through reduced time for work preparation). Thus, Production Planning and Control (PPC) in project manufacturing is facing new challenges. This applies in particular to complex assembly processes that are characterized by human work. Stochastically influenced process times are inherent in the process due to the fluctuating individual performance of humans and will, therefore, continue to exist in the future. There is also a low level of interaction and data availability between PPC in this domain. Representative examples of the characteristics mentioned above are the final assembly of customer-specific machine tools, printing machines or photovoltaic systems, in which several complex projects with individual objectives compete for resources. From a scientific point of view, project planning and control problems under uncertainties belong to the problem class of Stochastic Resource-Constrained Multi-Project Scheduling Problems (SRCMPSP). A solution strategy for this problem is stochastic scheduling without a baseline schedule, which is largely a novelty in the area of project scheduling. In our research project Hybrid PPC, we research heuristics for decentralized scheduling with an evolutionary simulation based optimization approach.

In this paper, we present the research background in Section II and the scope of the research project in Section III. In Section IV, we have a detailed look on the challenge heuristic and solution robustness and show our first steps regarding modelling. The paper concludes with a short summary in Section V.

II. RESEARCH BACKGROUND

Current PPC developments for mastering the challenges in a dynamic production environment are promising. In particular, the comprehensive decentralization of production control can enable the compensation of stochastic influences and process uncertainties while simultaneously improving logistic objective values [2]. So-called Cyber-Physical Production Systems (CPPS) are prerequisite in many approaches (e.g., adaptive scheduling approach [3], static scheduling policy [4]). However, the permanent automatic data acquisition and availability required for such systems is currently only partially feasible and will remain subject of research and development for the next few years [5]. The technical implementation [6] and acceptance of a continuous digital recording of human work is also unclear [7].

However, in order to use the advantages of new approaches in decentralized control, strategies are required that can be implemented with low data availability and interaction.

From a conceptual point of view, there are various approaches for such a decentralized control. For process control, mainly automatically generated heuristics [8] in form of Composite Dispatching Rules (CDR) are used and applied in various PPC concepts. Simply stated, CDRs are attributes calculated according to a rule from the information on the product, process, resource and system. While automatically generated CDRs are widely used in job-shop scheduling [8], applications of automatically generated CDRs for the solution of the Resource-Constrained Project Scheduling Problem (RCPSP) [9] and especially for the solution with a decentralized control for SRCMPSP are rather rare in literature. We can only guess the reasons for this. While the job-shop environment is traditionally stochastic, the RCPSP environment is also increasingly stochastic. Classical solutions for RCPSP by generating a baseline schedule are no longer effective and the interest in scheduling without a baseline schedule increases. One possibility for efficient scheduling without a baseline schedule are those CDRs. In addition, the SRCMPSP is more complex (e.g., more complex precedence constraints, larger

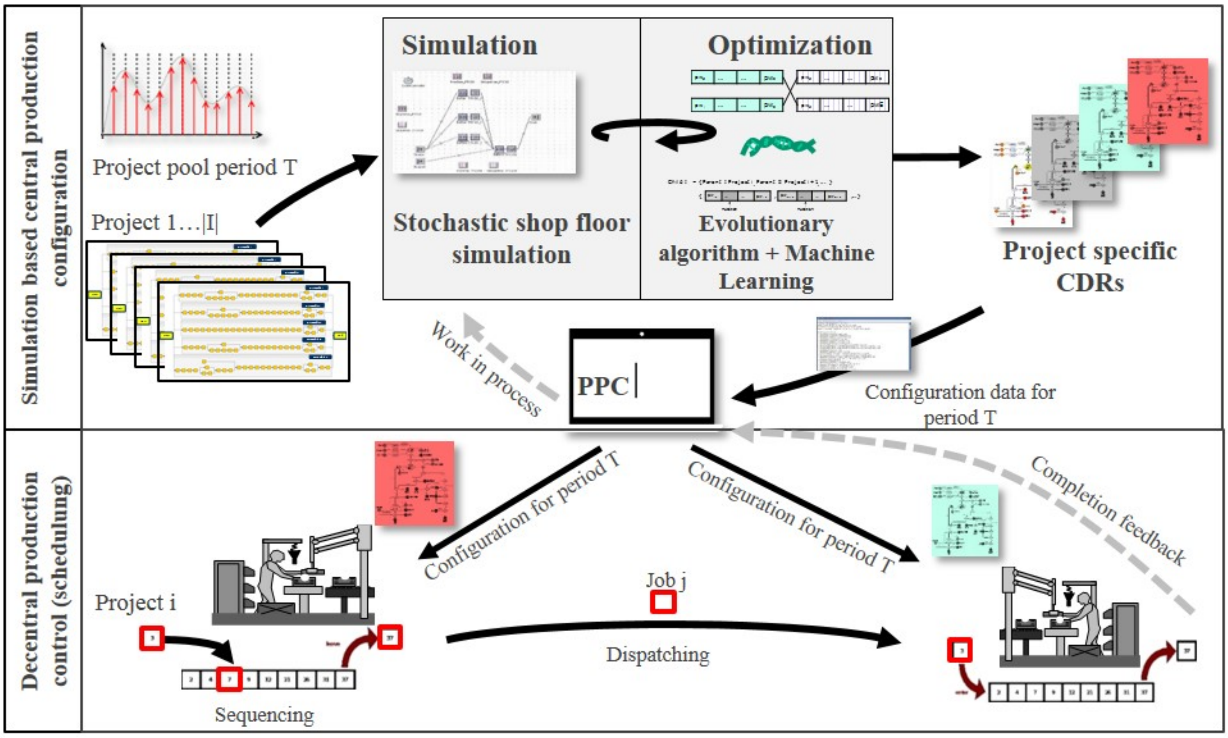

Figure 1. Proposed Hybrid PPC approach

problem size with up to 10 projects with up to 1000 jobs and up to 50 different resources) than the job-shop problem, which leads to increased requirements for PPC strategies.

III. Research Project Hybrid PPC

In order to distinguish our research from existing research in the field of decentralized control strategies due to lower data availability and interaction, we focus on the development of a method for the configuration of a CDR, which is valid for a limited period. We name this heuristic robustness. This CDR should be able to compensate process uncertainties autonomously.

In our research project *Hybrid PPC* we address different challenges and goals of the mentioned stochastic project scheduling problem (extract). We strive for the following goals:

- Best possible compensation of disturbance variables and stochastically influenced process parameters
- Multi-objective optimization: Differentiated optimization of project-specific and production system objectives
- Use of practical and easy to collect information in the production system as data basis for CDRs

To reach those goals, the following challenges arise:

- Benchmarking SRCMPSP
- Heuristic Robustness: Defining Evaluation strategies
- Investigation and applications of computational fast algorithms for generating CDRs

As mentioned, the two core components of the proposed Hybrid PPC approach is the central, simulation based configuration [10] and the decentralized control with CDRs (see Figure 1). The input for generating the CDRs is therefore a production scenario with stochastic variables, e.g., processing times, and a predefined time horizon. Based on this scenario, the central stochastic simulation starts with firstly randomly generated CDRs. Both the representation of the CDR (requirements low computation effort) and the selection of attributes (local attributes) are part of our research. In order to take advantages of different representation types, we see potential in the combination of rule-based and parameter-based representation and additional in the development of specific scheduling policies (e.g., while queue length < x, then FIFO). For improving the CDRs, evolutionary algorithms are conceivable.

Further, we want to use machine learning to generate initial solutions of CDRs (reduce computational effort) and these specific scheduling policies. Therefore, we want to derive the input parameters for the generation of the CDR based on similar model parameters. Methods of supervised learning are of particular interest here. Central configuration results in the CDR with the best statistical objective value of the different stochastic scenarios. These CDRs are transferred to the production resources and are used decentralized for scheduling. The specification of the size of the project pool / period length in correlation to heuristic robustness is also part of our research. This process is comparable to the transfer of the production schedule to production. Various options are conceivable for technical implementation. The minimum feedback quality refers to the completion of an order so that the work in process can be estimated. The success of the project is measured by whether the considered objective values are improved compared

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to achieved objective values of current used strategies (e.g., priority rules, list scheduling).

IV. Addressed Challenge Robustness And First Steps

A. Challenges of Robustness

In our research project, we define the robustness of heuristics to solve SRCMPSP as the capability to compensate disturbances and data uncertainty. The compensation of the disturbance correlates with the objective fulfilment. Therefore, we consider statistic values of the objective functions, so that one can also speak of solution robustness here. A low standard deviation is an indicator of high robustness.

The individual project objectives are usually in conflict with the objectives of the shop floor (see Figure 2). The first challenge is to choose the appropriate statistic for the objective functions. Usually only mean and standard deviation are considered. We also investigate other statistic parameters (e.g., range, median) if they are suitable for optimizing the objective values.

The second challenge is to find an evaluation strategy for these objectives. One concept to find a compromise could be pareto dominance [11]. However, this results in a high evaluation effort and reducing computational effort is also necessary. As an example, 10 projects with 5 objectives each means a total of 50 objective functions.

Looking on a first experiment based on previous work [12], we can underline the complexity of defining heuristic and solution robustness. For the experiment, we chose representative models of the Multi-Project Scheduling Problem Library (MPSPLIB) [13] and some industrial examples (complex printing machines). The objective function was Total Project Delay (TPD, sum of delay of all projects). Comparing mean and standard deviation of objective function values for different optimization strategies (single, pareto ranking) shows the effects in Table I. While a single optimization leads to good results for the considered objective and to bad results for the not considered objective, the pareto optimization leads to a good compromise (see Figure 3). The ratio of improvement to deterioration between the strategies is very different.

Concluding, how standard deviation and mean value correlate in the solution space cannot be determined trivially. Thus, the effects of achieving better results in one objective value on another objective value cannot be determined and are model-dependent. However, it is necessary to define additional measurements for heuristic and solution robustness according to schedule robustness [14].

B. Model description

As mentioned earlier, our problem class is a SCRMPSP. We base the description on Kolisch instances [15], which we extend by multi-objectives, setup times (based on job types), stochastically distributed job duration and resource capacity. To describe stochastics, we use examples from literature and practice. For example, the assembly time of assemblies for the interior fittings of ships is logarithmically normally distributed.

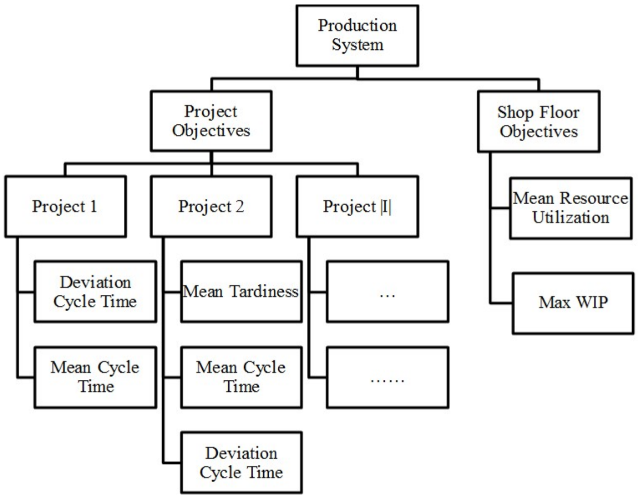

Figure 2. Shop floor objectives vs. project objectives

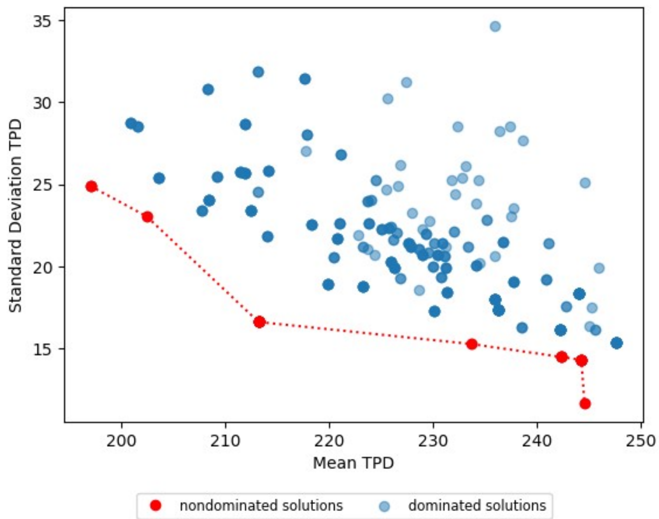

Figure 3. Result of pareto optimization (example)

The coefficient of variation is up to 0.9, which means a high uncertainty. The final problem description contains a production system with global resources and projects. Those projects comprise a list of jobs, an objective and project-local resources. Each of the jobs has a job type, a number of modes and a list of successors. A mode determines the duration and required resources of the job. A resource has a maximum capacity. Both duration of a mode and capacity of a resource can either be concrete, or stochastically distributed for some distribution.

C. Reproducible benchmark library

One of the challenges mentioned earlier is to benchmark an SRCMPSP and the comparison of different solution approaches for that problem. Our vision is to provide a benchmark architecture similar to the MPSPLIB [13]. However, the question remains: how to provide a suitable input to other participants solving a given problem instance? One can either provide stochastic distribution information, or provide

TABLE I. MEAN AND STANDARD DEVIATION OF TPD.

Model	Optimization strategy [1]					
	Mean TPD		Std TPD		Pareto TPD	
	Mean	Std	Mean	Std	Mean	Std
j30_a2_nr1	**41.3**	9.1	47.1	**6.4**	42.9	8.47
j30_a2_nr2	**54.8**	15.3	57.3	**11.6**	54.9	12.10
			⋮			
PM_1	78.71	6.49	86.58	**3.68**	**74.73**	7.95
PM_2	**57.84**	4.93	69.03	**1.97**	64.95	3.93
PM_3	**65.29**	8.18	84.9	**3.11**	68.18	5.72

[1] Considering different objective strategies: mean, standard deviation (std) and pareto-optimization (mean and standard deviation) of TPD (time units), evaluation of mean and std for each strategy

"scenarios", i.e., a finite number of concrete values for all stochastically distributed values. The former is more concise, but not necessarily comparable whereas the latter is comparable, but more verbose.

D. Current status

We began to implement a process for generating problem instances of our problem class (see Figure 4). For this, an existing problem generator (ProGen) [15] is used to generate a base problem. This description is parsed into and together with the missing information like stochastic distributions, the problem is extended to be fully compliant with the problem class of SRCMPSP. The current process ends with persisting that description. Next steps are a) to find ways to compute one solution for the now extended problem, and b) to find strategies to generate heuristics, as described earlier.

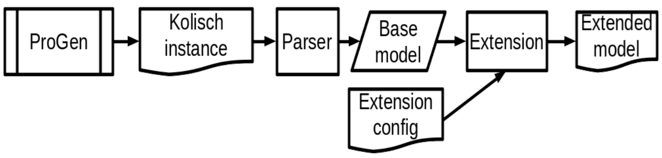

Figure 4. Extension process

V. CONCLUSION

In this paper, the research project Hybrid PPC was presented. The project takes up the PPC problem in customer-oriented project manual manufacturing and deals with fundamental questions of both scientific and practical relevance. The approach is the central configuration of a decentralized control system based on various algorithms. Therefore, we have developed a complex model of the SRCMPSP. We are currently developing an evaluation model by examining various statistical parameters of the objective function values to describe and investigate solution and heuristic robustness. Our next step is the development of a scheduler with the requirement of short computation time. In parallel, we investigate possibilities to reuse the simulation data with the aim to save computation effort. Machine Learning algorithms are promising to find correlations between models, solution approaches and objective function values based on large data sets.

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