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16.6 Achieving resource- and energy-efficient system optima for production chains using cognitive self-optimization

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Abstract

Production systems no longer have to pursue one, but a set of goals. Classic optimization regarding lead time or capacity utilization is still sought after, but was extended by factors such as energy consumption or use of cooling lubricants. Thus the models of dependencies and system behavior become more complex, hampering optimization by classic algorithmic approaches.

One subdomain of the Cluster of Excellence "Integrative Production Technology for High-Wage Countries" examines the potential of cognitive self-optimization as a way of handling technical complexity. This paper analyses the constraints and dependencies that have to be considered to find overall optima for process chains and gives an assumption of the associated complexity. This builds the base for future implementations of self-optimization to boost overall resource- and energy-efficiency in process chains. Furthermore, examples are presented on how optimization can be realized by using cognition and self-optimization.

Keywords:

Self-optimization of process chains, complexity of Job Shop Scheduling problems, production system optima

1 INTRODUCTION

The determination of optimal sequences of jobs that need to be conducted on a group of machines is called "Job Shop Scheduling" (JSP) and has been one of the classic optimization tasks in mathematical production research ever since [1]. The basic problem of JSP can be described as follows: For a specific group of components, all with individual subsequent production steps, an optimal overall sequence of conducting these on a specific group of machines, needs to be found. Usually, the overall production time ("makespan") is the optimization goal that is meant to be minimized. An example of a 3-machine 3-component problem, where each component has to be processed on each machine, but in differing sequences, is presented in figure 1.

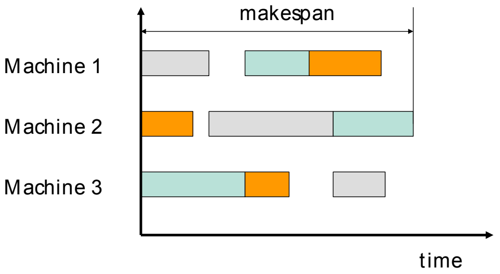

Figure 1: A basic job shop schedule

Every one of the nine jobs has a specific length, cutting down the problem to finding the optimal starting time for each job, determined by the completion of the previous job and the availability of the machine. Even though these problems often appear quite easy, the mathematical complexity connected with finding an optimal (or, at least, "good enough") order, rises exponentially. Hence, for problems including more than four to six machines and components, instead of systematically testing all possible sequences ("brute-force") regarding the desired objective (makespan, capacity usage etc.), other approaches have to be considered. As for the classic JSP discussed above, heuristics such as the nearest-neighborhood algorithm [2] or more advanced approaches such as artificial neural networks [3], agent-based-networks [4], genetic algorithms [2] or ant-colony-optimization [5] have been used successfully.

When considering more options for each job, e.g. the process velocity to influence energy consumption, the number of options (and thus the mathematical complexity) manifolds. Still, such variables need to be regarded to find overall optima for process chains. Therefore, this paper analyses the constraints and dependencies that have to be considered and gives an assumption of the associated complexity. Furthermore, examples are presented on how optimization can be realized by using cognition and self-optimization, which is one of the main topics of the Cluster of Excellence "Integrative Production Technology for High-Wage Countries" in Aachen.

2 OPTIMIZATION GOALS FOR PRODUCTION SYSTEMS

Due to a study conducted in [6], the lifecycle cost of a machine tool is mainly composed of operating expenses, as the purchase price only makes up for 20% of the total. Furthermore, 40% of the operating expenses are caused by

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the consumables electrical energy, coolant lubricants and pressurized air, as shown in fig. 2. As their consumption strongly depends on the process parameters, the consideration of machine variables in scheduling has an enormous influence on total costs of a process chain as well as its resource- and eco-efficiency.

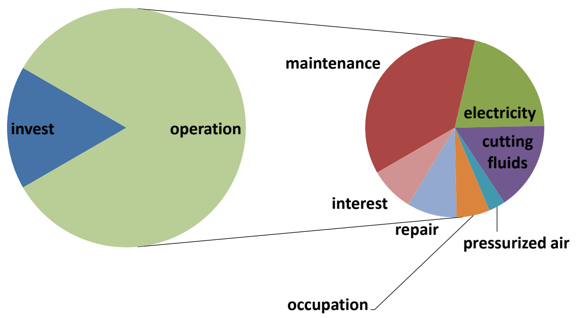

Figure 2: Lifecycle-cost for a tool machine [6]

Besides economic considerations, ecologic objectives can be included into the goal system of production processes [7]. The impact assessment and the evaluation of process inputs and outputs can be achieved by metrics such as the carbon footprint. Ecological assessments have been widely in use in certain industries with a high amount of resource consumption and pollution potential, e.g. energy production or the chemical industry. Several examples of the integration of LCA methods for production processes into multi-dimensional optimization approaches can be found in the scientific literature [8], [9].

Including single machine variables and behavior into Job Shop Scheduling indicates three major challenges: optima for single machines and complete process chains may differ, the determination of in- and outputs for each machine model need to be known and the complexity of the planning algorithm manifolds. Hence these issues are discussed in the following sections.

2.1 Optimization of single processes vs. process chains

For a single process, the economically and - most of the time also - ecologically optimum operating point for a single tool machine is the maximum operating speed. This is mainly due to the high amount of auxiliary units, e.g. pumps or electronics, which constantly consume electrical energy regardless of the machine being idle or running at full speed [10], [11]. For an entire process chain, priorities can differ: E.g. the electricity cost for industrial companies is normally determined by two major components: the total energy consumed, and the maximum load peak required. So instead of having several machines operating at maximum speed, it can be more cost-efficient to reduce process velocity when operating close to an energy peak load [12].

The same metric applies to the consumption of cooling fluids and tool lifetime for chipping operations such as milling or drilling. Most machines use closed cycles, so that fluids are not lost but filtered and re-used. Still, a large share is lost due to vaporization [13]. The need for cooling corresponds to the heat development at the tool cutting edge and thus the material removal rate. Reducing cutting speed where possible can minimize the need for cooling lubricants and extend the tool life. On the other hand, it increases the total energy consumption [10] and, if the decelerated process causes subsequent jobs to start later, deteriorates the overall process chain efficiency.

Thus, the optimum for single processes and complete process chains can differ, depending on the system boundaries and the applied metrics for the evaluation of an operating point.

2.2 Machine tool behavior and dependencies

The prediction of machine tools behavior e.g. regarding their energy consumption has been subject to various scientific projects and approaches (see [14], [15], [16] or [17]). Results show that these models are able to predict the machine behavior within very close limits and thus can contribute to realize process optimization. Fig. 3 illustrates some of the dependencies of the resource consumption and output parameters of a cutting machine from in-machine units and the input control variables. More important than the exact determination of each dependency is the insight that when starting to consider in- and output parameters for each job to determine e.g. the consumption of electrical energy, the original Job Shop Scheduling problem expands significantly.

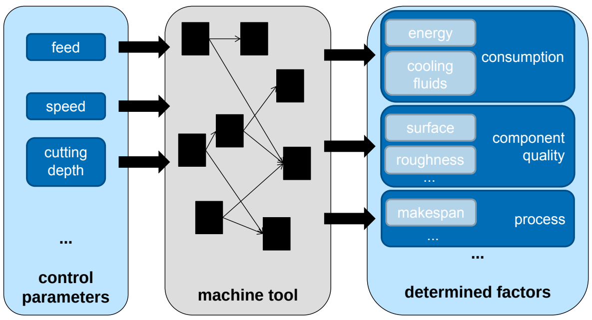

Figure 3:control parameters and dependend factors for a machine tool

For the basic scheduling problem, the sequence of jobs was the only focus, thus reducing the optimization to only one parameter per job – its position within the schedule. Considering machine behaviour models as presented above now leaves a whole set of options for each sequence. To evaluate the implied consequences for scheduling algorithms, the expanditure of the original problem is examined in the following section.

2.3 Complexity of the central planning approach

When looking at the intermediate units and interdependencies presented in the section above, it becomes clear that deterministically planning the control parameters for each machine even on a medium sized shop floor becomes more complex.

A classic job shop scheduling problem consisting of 10 machines and 10 components was introduced by [18] in 1967 and has since been a major benchmark for solving algorithms. In 2009, Schwindl [19] calculated the number of possible sequences for this problem to be $(10!)^{10}$ (= 3.95×10^{65}), blocking the then known world's most powerful computer for several millions years if trying to solve if by a "brute force"-approach. Even though near-optimal sequences for this classic JSP-benchmark can be found within minutes using advanced approaches such as genetic algorithms, it becomes clear that the complexity quickly manifolds with the number of machines, components or other options.

When considering machine parameters, the number of possible set-ups for each sequence rises. As discussed above, a machine tool has several input parameters (m), each of which has several values (n). To reduce the number of options, the input parameters are regarded as discrete values, e.g. low-medium-high, or 1-5. So for a job shop scheduling problem with k machines and l components, the number of possible set-ups for each sequence adds up to:

$$(n^m)^{k\times l} = n^{\,m\times k\times l}$$

Taking the benchmark problem into account (10 machines and 10 components, adding up to 100 single jobs) and assuming machines with three parameters (e.g. feed, speed and cutting depth), each with only three values (low – medium – high), this ends up to $1{,}37\text{x}10^{143}$ possible set-ups for each sequence. As shown by [19], there are $3{,}95 \times 10^{65}$ possible sequences for this standard JSP-benchmark.

As discussed in section 2.1, most processes will normally be conducted at the maximum possible rate and reduced only when necessary. Still, as the number of machine parameters can be higher and discretization will normally be conducted in much finer steps than three, complexity can be said to be beyond the reasonable application of "brute force"-approaches. Hence more advanced approaches to realize the inclusion of machine parameters and models into Job Shop Scheduling are discussed in the following section.

3 APPROACHES TO INCLUDE RESOURCE CONSUMPTION INTO JOB SHOP SCHEDULING

First approaches to include the resource consumption of tool machine into Job Shop Scheduling can be found in [20], [21] and [22]. As the complexity of the induced mathematical problems rises [21], more advanced approaches such as combined local search algorithms [22] or ant-colony-optimization [23] are applied to find more optimal solutions.

To overcome the complexity problem when combining Job Shop Scheduling and resource consumption as described above, distributed decision making with agent-based algorithms [24] and self-optimization appear to be two promising approaches. In the following section, these are examined more closely.

3.1 Agent-based distributed decision making

When handling job shop problems with a high complexity, one promising approach is the development of distributed, agent-based networks [4]. A good introduction to this topic can be found in [25] and [26]. First attempts of distributed, agent-based decision-making go back to the 1980s [27]. The number of its successful applications has since multiplied, a good overview can be found in [28] and [29]. Advantages of the distributed, agent-based network approach are its robustness and the ability to find near optimal solutions even for complex problems within an acceptable calculation time [30]. The emergence of cyber-physical systems in the scientific spotlight underlines the future role of this approach, as CPS mainly resemble distributed networks of interacting and communicating machines [31].

Another advantage of distributed networks is the possibility to add and withdraw subsystems (e.g. single machine tools) dynamically, e.g. in case of a technical failure. So when a single machine within a cooperating network breaks down, the remaining production system can continue without rearrangement of the control structure. This, of course, requires the existence of standardized communication protocols. Furthermore, agents in distributed networks can be equipped with the ability to learn, thus react to changed boundary conditions and system statuses. Learning is always conducted by comparing the achievement of an action and its intended goal. Thus, the goal needs to be known and quantifiable.

3.2 Self-optimizing process chains

Self-optimizing process chains resemble another promising approach to overcome the complexity problems discussed above. A good introduction to the concept of self-optimization as a way of setting up the control structure of more autonomous machines can be found in [32]. Basically, it resembles a procedure of three major steps:

i. analysis of the current system situation,
ii. determination of (new) system objectives and
iii. adaptation of the system's behavior to the new surrounding conditions [33].

System objectives can either resemble single physical units such as vibration [34] or a specific torque [35] or multi-dimensional goals, e.g. a combination of the handling characteristics of a systems and its energy consumption, requiring multi-objective decision making and optimization [36].

The concept of self-optimization has been applied successfully to the control of demonstrator objects such as trains and robots [32] as well as real production processes such as laser resonator alignment [33], laser cutting or weaving [37].

Self-optimization can be used on various levels: on the level of a single machine, it can be applied to influence its parameters to achieve a local process optimum, as in the examples discussed above. On a shop floor or even factory level, the concept of self-optimization can help to reduce planning efforts and complexity by offering the option of cascading control loops [38], [39]. Instead of taking all decisions on one level, e.g. the factory control, goal vectors are used as a way of communicating between the different control loops, as presented in figure 4: On a factory level, certain jobs, boundary conditions and goals are assigned to a process chain. Here, these are enhanced with further information and split to be assigned to different machines. The tool machine will thus be allowed to optimize itself within its constraints and boundary conditions to achieve its assigned goals as good as possible. This way of arranging self-optimization on different levels within the factory infrastructure resembles the approach of cascading quality control loops as can be found in [40] and [41].

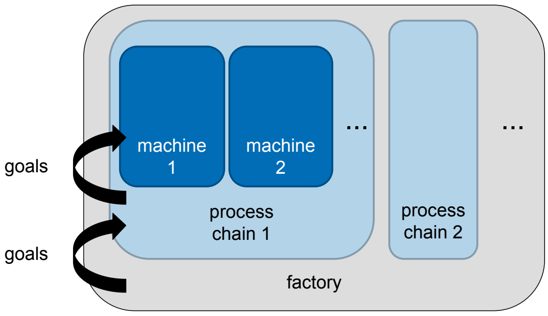

Figure 4: schematic diagram of cascading, self-optimizing control loops

An example of a goal vectors could be a specific job with the additional constraint not to exceed a certain peak load, total energy and lubrication consumption as well as a latest time of job completion.

4 NEED FOR FUTURE SCIENTIFIC WORK

As discussed above, distributed, agent-based decision making and self-optimizing process chain optimization can be a successful way of overcoming the induced complexity of a job shop scheduling problem that is expanded by modifiable machine parameters and thus contribute to achieve more global process chain optima.

Implementing these approaches causes two major demands that will thus be subject to further scientific work within the Cluster of Excellence: a well-known and quantifiable goal system and structures and protocols for inter-machine-communication.

4.1 Multi-dimensional goal systems

The major requirement for any kind of optimization algorithm is a known and quantifiable goal. To achieve a general optimum for a process chain, a larger group of goals needs to be considered. In addition to the makespan, that typically formed the optimization parameter for classic scheduling approaches, other process characteristics as e.g. resource consumption of electricity or cooling fluids have to be taken into account. Alongside a costing approach, these can also be evaluated in other metrics, e.g. reflecting ecological considerations. Thus, goals with differing physical units and scales would have to be compared to one another. Representing all of these goals in a quantifiable way requires the use of a multidimensional goal system that can be interpreted and used by a computer-based system or network. One major focus of the future scientific work thus needs to be the development of a complex goal system that represents economic, ecologic and socio-economic goals, resembling the three major perspectives (and thus assessments) that are taken into account when evaluating processes or products. A goal system has to enable trade-offs between the different performance measures and goals indicated by those assessments in a quantifiable way to support multi-dimensional decision making and optimization.

4.2 Communication networks and protocols

As discussed above, the application of self-optimizing process chains and distributed, agent-based production networks manifold the need for inter-machine communication. Different machines, factory and administration levels and networks have to exchange information and communicate goals and restrictions to enable cooperation. Thus, one focus of future scientific work will be to research effective communication networks and protocols to enable information exchange between single machines as well as superior planning and administration systems.

5 CONCLUSION

Production systems no longer have to pursue one, but a set of goals. Classic optimization regarding lead time or capacity utilization is still sought after, but needs to be extended by factors such as energy consumption or use of cooling lubricants to achieve overall system optima. Thus the models of interconnections and system dependencies of single machines and machine networks become more complex, hampering optimization by classic algorithmic approaches. Promising approaches to overcome the induced complexity, such as distributed agent-based networks and self-optimization, exist. Finding ways to enable inter-system-communication and developing goal systems for the evaluation of overall system optima are two major issues that will be taken into the focus of future scientific work.

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