Simulation-Based Multi-Criteria Optimization of the Time-Dependent Energy Consumption of Manufacturing Process Chains

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IF YOU HAVE ONLY 2 MINUTES ...

The turnaround in energy policy is an ambitious intention for the German society. Especially the efficient usage of available energy sources, like wind and solar energy, is a big challenge. However, one solution to tackle this problem is the smart demand management. That means, to adjust the demand to the energy supply.

Nowadays, in the field of production and logistics, economic and technical terms are in the main focus for process control. In this work the time-dependent energy consumption is considered additionally.

On a reference manufacturing process chain (pc), different approaches for energy controls are tested. The first, so called heuristic approach, generates the control values for the process to satisfy a given energy curve based on the process states and heuristic knowledge. The second approach generates control values using a simulation based optimization with a Genetic Algorithm provided by the Global Optimization Toolbox within MATLAB/Simulink.

With different experiments the controls are verified and the effects of the process shifting are studied.

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SOME MORE DETAILS, EXAMPLES AND RESULTS

Experiment Design Using the Concept of EF

In the project several experiments are implemented using the concept of EF. The set of MUS comprises two pc, three controls and a variant without control. For the study of a particular experiment, one EF gets consecutively coupled with several MUS. Using this approach, different controls can be compared easily.

In this experiment 48 parts were manufactured with pc1 (see box 2). With the heuristic control the power curve of the pc, $P_{tar}(t)$ is fitted to the targeted power curve $P_{tar}$. Overstepping $P_{tar}$ was not allowed using the heuristic control. As a result, the time delay is 10 hours. The meta-heuristic control optimizes the fitness value (see box 3). A limited exceeding of $P_{tar}$ by $P_{tar}$ was allowed to achieve a higher profit.

CONCLUSION AND OUTLOOK

• Both investigated heuristic control strategies delivered good results for both process chains in short computation time on a standard PC with 4 cores (1 to 3 minutes).
• Of course, the amount of internal knowledge of a heuristic control influences the result quality.
• The heuristic control with internal energy maps (determined by pre-simulations) delivered better results than the meta-heuristic optimization-based control using a genetic algorithm (see previous box).

The meta-heuristic optimization-based control works only for process chains with few process operations, because the calculation of optimized switching times (box 3) needs a high amount of computation time (more than 2 hours for the experiment in the previous box).

Outlook:
• Verifying the heuristic control strategies with more complex process chains.

PROCESS CHAIN WITH HEURISTIC CONTROL

Figure 1 shows the reference process chain (pc) with a superordinated heuristic control. The pc contains the basic processes: turning, hardening, tempering and grinding. The heuristic control strategy generates the control values based on the process states, internal process knowledge and the targeted power curve $P_{tar}(t)$.

Process state information are for example the buffer stocks and the power needed over time of the single processes. The power demand of the single processes has been determined before using simulation for different process parameter. That means, we determined an energy-related map for each process.

SIMULATION-BASED OPTIMIZATION APPROACH FOR CONTROL

The simulation-based optimization generates control values $u(t) = ( spoiler, force, pressure, pressure)$ by the use of optimization of fitness value $C(t)$. The control values, i.e. the optimization parameters, are switch on times for each single process operation. The fitness function calculates the profit of the process chain using different weighted command variables. For numerical optimization, the Genetic Algorithm of the Global Optimization Toolbox in MATLAB/Simulink is used.

CONCEPT OF EXPERIMENTAL FRAME

To test and verify different pc and controls, several experiments are studied. Therefore, model and experiment are separated in Model under Study (MUS) and Experimental Frame (EF). The generator defines the input variables for the MUS during a simulation run and the MUS delivers the output variables to a transducer, which calculates interesting variables based on model outputs, such as a fitness function value. The acceptor stops the experiment, if a stopping criteria is reached.

Figure 1: The process chain with superordinated control.

Figure 2: The simulation-based optimization approach as control.

Figure 3: Experimental Frame with its elements and Model under Study with pc and control.