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Increasing energy efficiency in production environments through an optimized, hybrid simulation-based planning of production and its periphery

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Abstract

This research aims to develop a novel planning tool able to increase both the energy efficiency and general performance of production systems using a hybrid-simulation based, multi-criteria optimization, with this particular paper focusing on the optimization method. Lacking necessary planning tools for an energy aware production planning and control, companies are unable harness the associated optimization potential. State-of-the-art tools are not able to sufficiently consider interactions between the discrete system behavior of material flow and the continuous thermal-physical behavior of equipment. This paper presents a planning method addressing this deficiency. The developed genetic-algorithm based optimization module optimally fits the requirements.

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Keywords: energy efficiency; production planning; optimization; hybrid simulation; multi-criteria metaheuristic optimization

1. Introduction

Long term trends of rising energy costs, together with a societal drive towards notions of sustainable living plus pressure from the political domain, facilitate the need to increase the energy efficiency of production processes. The basic definition of energy efficiency in the context of production is the ratio between the value-added output of a production system and the necessary energy input [1]. The industrial sector is currently responsible for 31% of the annual energy demand and 36% of the CO_2 emissions globally [2], rendering energy efficiency an important goal. Thus, sustainable manufacturing has become a new paradigm for manufacturing enterprises [3].

Thus, planning tools providing decision support for this new set of goals are necessary [4]. A demand analysis by a large EU-FP7 research project has identified a need for ICT tools that enable companies to effectively reduce CO_2 emissions. Market research by McKinsey has estimated the global market for Information and Communications Technology (ICT) solutions supporting the energy aware planning to be around 15 billion EUR by 2020 [5].

Studies show that energy efficiency considerations should be an in integral part of Enterprise-Resource-Planning (ERP) and Manufacturing Execution Systems (MES), with simulation based approaches suggested to be the most promising methods [6]. However, currently there is a lack of practically applicable planning methods.

In order to address this deficiency, this research is meant to develop a novel planning tool that increases both the energy efficiency and general performance of production systems using a hybrid simulation-based optimization approach. This particular paper focuses on the optimization method. The research is embedded within a larger research project comprising multiple academic fields as well as implementation partners for software development and industrial enterprises as application partners.

The paper is structured as follows: First a summary of the requirements for a software planning tool for production planning and control (PPC) purposes is presented, followed by

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a brief overview of related work. After that, the results concerning the underlying methods for the planning tool, hybrid simulation and the optimization – the main focus of this paper –, are presented. Finally, the results are conflated and discussed.

2. Requirements for the planning tool

The requirements for a planning tool have been deducted from an analysis of relevant literature, supplemented by expert interviews with managers from the application partners within the research project. According to the findings of a large EU research project, based on interviews with 106 international experts, the tools will have to consider both conventional economic planning goals and energy and resource efficiency simultaneously. The planning should be integrated into the existing ICT and the use of detailed simulation models is recommended [5]. Li [7] stresses the necessity for a generic structure to make the tools available for different application environments. He [3] also emphasizes the need to consider all relevant energy flows and their interdependencies. Concerning the underlying methods, Thiede – among others – declares simulation to be the method best suited to provide the necessary planning support [8]. An automatic decision support function, i.e. in the form of an optimization module, is another major request from prospective industry users.

3. Related Work

In this chapter, a brief overview of related work will be introduced. This comprises two major aspects: the hybrid simulation and the optimization.

3.1. Simulation & simulation based Planning approaches

The basic concept of a dynamic simulation is to create a digital model of a real-life system, featuring all relevant characteristics, and to then use that model to conduct experiments in order to gain insights into the system behavior or to optimize and develop plans for the system [9]. Material flow and the processing of orders is simulated utilizing a discrete event simulation (DES), while the thermal-physical behavior of machines and equipment is simulated in continuous simulation environments that basically solve differential equations (Differential Equation System Specification – DESS). One of the most advanced simulation based concepts for planning tools in the field of energy aware planning is Thiede's approach based on a multilevel-simulation [10]. This concept combines multiple simulation environments in a co-simulation, in which the subsystems are modelled either in a DES or DESS environment. The sub-simulations are coupled at certain points during the simulation run and provide a certain level of integrated modelling. However, the level of integration necessary to comprehensively represent the interactions between the energy system and the production and material flow is practically impossible to achieve with a co-simulation. This requires an integrated hybrid simulation, enabling both a continuous and discrete behavior simultaneously.

3.2. Optimization & simulation based optimization

Optimization methods comprise optimization algorithms that are able to find optimal solutions for problems with a limited complexity and optimization heuristics that are able to find approximate solutions, if exact solutions cannot be found; these are called NP-hard problems. Within heuristics, there are special heuristics dedicated to a certain problem category in operations management and metaheuristics that serve as generic algorithms for a broader range of applications when dedicated heuristics are not available [11]. Most complex optimization tasks, especially if the optimization utilizes a simulation as an evaluation function, as in this research, feature multiple local optima. This requires the algorithms to not „get stuck" in local optima, in order to arrive at better solutions eventually [12]. The metaheuristics can be discerned in algorithms based on iterative local search (LS) and generative population based methods (PS) [13]. Most of these heuristics mimic natural processes, i.e. imitating animal behavior, evolution in biology or the cooling of materials.

The optimization problem in this research is mainly the *scheduling and sequencing of orders*, thus representing a permutation flow shop sequencing problem (PFSSP), extended by the optimal control of production equipment and equipment in the periphery. For optimization in production scheduling applications without the energy aspect, Pochet gives an overview of approaches based on mixed integer programming [14]. Due to the increased model complexity in the case of energy aware planning, there are examples of approaches based on the Genetic Algorithm (GA) [15] and Rager [16] utilizing the GA for a simulation based approach in a case similar to the projected application of this paper. None of the existing optimization methods features the more complex hybrid simulation developed and used in this research, thus a customized optimization method has to be developed.

4. Hybrid Simulation

The characteristics of the simulation determine the requirements for the optimization, which will utilize the simulation as an evaluation function, thus the following will give a brief overview of the development of the hybrid simulation, although the main focus of this paper is on the development of a suitable optimization method.

Originating from the work of Zeigler, system specifications for a hybrid simulation have been developed – DEV&DESS and hybrid Parallel Discrete Event System Specification (PDEVS) [17]. These specifications provide a hierarchical and modular system definition, consisting of *atomics* – the basic building blocks describing dynamic system behavior – and *coupled* – describing a system behavior with interacting components that can either be "atomics" or other "coupled". The formalisms describe, how events are to be handled and how ordinary differential equation solvers (ODE) are called, to model both the discrete and continuous system behavior. The approaches have been evaluated in the simulation development phase of this research and the PDEVS formalism turned out to be the most suitable option [18].

Based on the PDEVS formalism, a simulation implementation has been developed, together with a modelling approach. The corresponding modelling approach is based on "cubes" as building blocks of the simulation. Cubes are subsystems of the simulation usually representing units and machines in the real-world factory – i.e. ovens, rooms, technical building services (TBS) components – with consistent system boundaries for flows of energy, material and information. This is markedly different to the classic approach with different system boundaries for each simulation component. The universal modelling concept, together with the simulation method, allow for a modular modeling of any given factory equipment. A basic simulation model library has been compiled thus far, with cubes representing equipment in an industrial bakery, as well as those of an electronic manufacturer and machine manufacturers, including TBS components.

5. Optimization Module

5.1. Development procedure

The optimization was developed using a test case implemented within the hybrid simulation developed in this research project (cf. chapter 4). The test case is a simplified model of the actual production facility in an industrial bakery that will be implemented once the optimization module has been finalized. The simplification is designed to offer a controlled setting, where the optimization results can be checked and validated manually, while still providing the level of model complexity that the eventual use-cases in companies will feature. It comprises a production line with two process variants for the production of baked and deep-frozen rolls. The model, displayed in Fig. 1, features five major production machines and four conveyor belts with deflectors/junctions and storage components in the production and logistics system.

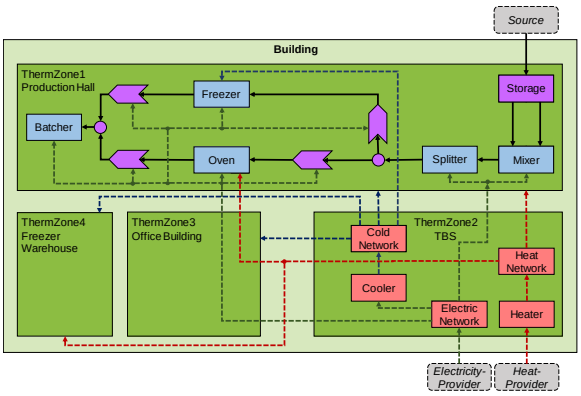

Fig. 1. Simulation model: structure plus material and energy flows.

Two of the machines – an industrial oven and a freezer – feature a distinct thermal-physical behavior. Concerning the TBS and energy system, there is a heater providing heat via a heat network to the industrial oven and the different halls/subsections of the factory building. The building itself is divided into four thermal zones, representing the main production hall, a room with technical building services equipment, an office building and a freezer warehouse – each of those zones is supplied with heat/cold and exchange heat with each other during the simulation. The simulation, validated with historical production data and energy measurements, was originally implemented in a Matlab® framework and has then been implemented (C++ based) and improved by a software implementation partner within the research project, thus providing the optimization development with a high-performance – concerning simulation runtime – version of the hybrid simulation.

The actuating variables for the optimization comprise the order release times, the operating times and modes for production equipment, including the machines, equipment in the production periphery and TBS components. This enables the optimization i.e. to pre-heat an oven, to determine an energy efficient order sequence and an optimal scheduling of orders with known delivery dates. Starting with an initial (set of) solution(s), the optimization uses the hybrid simulation to evaluate the performance of every solution, working towards finding a solution that optimizes a multi-criteria objective function.

Since none of the existing simulation based optimization approaches is directly applicable for this project, a comparative evaluation of potential metaheuristics is being conducted. The procedure consists of three phases:

- First, different metaheuristics that are suitable for complex multimodal (featuring local optima) fitness-landscapes are being tested with identical scenarios and with a default set of optimization parameters – the heuristics implemented in the Matlab® Global Optimization Toolbox are used.
- Second, the best performing heuristics from phase one are then enhanced and customized to provide an optimal fit for the given optimization task and model behavior and thus increase the optimization performance – again mainly concerning processing time, with processing time being one of the main factors for a practical application of the planning tool at the end of the project.
- Third, once finalized, the developed optimization module will also be implemented in the software implementation, alongside with the already implemented simulation, for an improved tool performance.

The metaheuristics compared in phase 1 are:

- Genetic Algorithm (GA)
- Particle Swarm Optimization (PSO)
- Simulated Annealing (SA)
- Pattern Search (PS)
- Multi Start Search (MS)

The test scenarios comprise: 3 simulation durations (1d, 7d, 30d), each with 2 production programs (small/large number of manufactured products – featuring 2 different product types with different process variants), with multiple runs for each scenario to handle stochastic uncertainty.

5.2. Defining an objective function

The optimization evaluates the system performance for each parameter set (each plan/solution) according to an objective function representing the management preferences of the planners. Through customizable weights the multi-criteria objective function both normalizes different feedback parameters – i.e. costs, delays and amounts of energy –, so that they are on a comparable scale, and prioritizes the part goals. For the optimization development, a simplified version of the objective function is used, defined by the industrial bakery that is the first application partner of the planning tool within the project. The function is defined as a minimization function.

$$f(x) = \omega_1 \sum_{i=1}^{n} (f_1(c_i)) + \omega_2 n_2 + \omega_3 n_3 k_1 + \omega_4 n_4 + \omega_5 t_{peak}\, n_{peak} \quad (1)$$

ω_1 - ω_5 ... part-goal weights
i … index for production lots
f_1… evaluation function for late deliveries and storage costs
c_i… lot completion time
n_2… accumulated lot lead times
n_3… accumulated overall energy usage
n_4… number of unfinished goods (goods not produced)
n_peak… accumulated amount of power utilization above a defined maximum power consumption threshold
t_peak… accumulated time of peak energy usage

The function f_1 calculates storage costs for goods finalized before the delivery date and penalty costs for delayed deliveries as a function of the order completion time.

5.3. Phase 1 – selection of suitable meta-heuristics

Fig 2 shows the results of the comparative test of metaheuristics with default options.

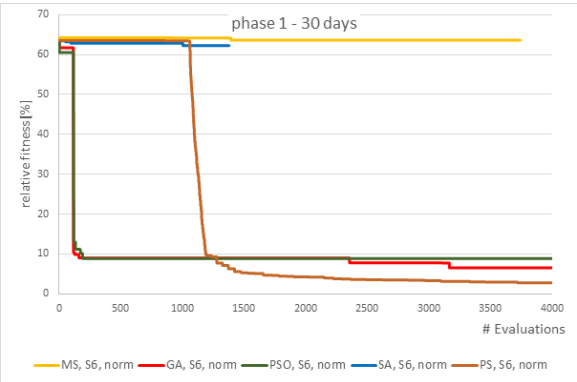

Fig. 2. performance comparison of heuristics – phase 1.

The results show the GA and the PSO performing well – since both are population based algorithms, the results are consistent while the results for the not population based algorithms are prone to stochastic fluctuations; some runs deliver good results while others arrive at weak results for identical scenarios. For simple scenarios (1-day simulated time and few products) PS and SA can beat the population based algorithms, but for more complex (in this case longer and containing more production lots) scenarios, the probability of good results drops drastically, thus making population based algorithms the better choice.

The GA shows the best overall behavior: the results for multiple runs for the same scenario are consistent and reliable, the relative goal-function improvement was among the two best performing algorithms in the panel. Its robustness in large search spaces with multiple local optima make it a good fit for the optimization task at hand plus, it lends itself well to a targeted tuning and customization within the search algorithm itself. Another advantage is the possibility to parallelize the simulation evaluations of one generation of solutions – with the simulation runtime being the biggest time optimization-runtime component, this has the potential to significantly increase the optimization performance of the planning tool. This also concurs with the findings of Rager [16], who used the GA for a similar task of a simulation-based optimization in the field of production planning, although for a less complex simulation model.

5.4. Phase 2 – tuning and customization

Having selected the GA for phase 2 of the optimization design process, we would like to give an overview of the basic algorithm first – cf. Fig. 3. The GA mimics the process of evolution in biology: an initial population (of solutions) is transferred to subsequent generations amid recombining and mutating characteristics of the parents and selecting the members of the subsequent generation, according to their fitness, as measured with the objective function [19].

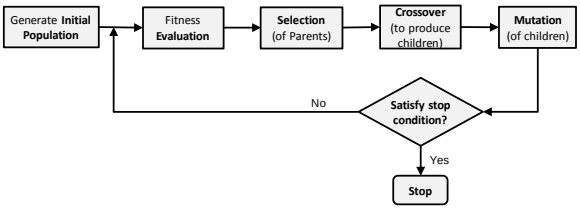

Fig. 3. Basic algorithm: GA.

One of the major problems the optimization metaheuristics faced in phase one, was the huge search space and the large proportion of bad or unfeasible solutions therein. The search strategy of most algorithms aims for a gradual improvement. If the vast majority of solutions is bad – i.e. not all products are being produced –, the subsequent punishment through the objective functions for practically infeasible solutions overshadows the feedback for gradual improvements. An obvious way to reduce the search space and especially to reduce the space with bad solutions, is to define constraints using specific knowledge of the model behavior. Still, those constraints must have an algorithmic character so that they can be integrated into the optimization module as general rules – the following restrictions proved to be useful:

- preventing overlapping lot time-spans on any machine

- time windows for operating times of machines ≥ smallest lot processing time for that machine
- for every machine: sum of all operating time windows ≥ minimal accumulated processing time of all production lots

These restrictions are based on the principle of setting multiple windows of operating time – each demarcated by start and stop times – for every machine, depending on the number of production lots to be produced. In addition to sensibly reducing the search space through constraints, tuning and customizing the GA itself was the second major tuning component – this comprised:

- implementing a **guided search** by adapting the operators of the GA
- integrating a **memory function** from the Tabu Search algorithm
- implementing a **mixed integer optimization**
- **hybridization**: combining the GA with the PS
- determining the **optimal population size**

A **guided search** is meant to focus the parameter changes of the optimization algorithm on the most promising changes. This, again, requires heuristic knowledge of the simulation model behavior – in this case we again used the operating time windows already introduced for setting restrictions to reduce the size of the search space. The guided search was implemented via the crossover operator of the GA as follows:

- the original function of the crossover operator is to combine characteristics of two individuals of the parent generation in order to generate one child with new characteristics – for the optimization problem in this research and the corresponding vectors, this would lead to a large number of practically unsound solutions, thus the function was altered to only feature a more sophisticated mutation, which actually performs the guided search
- changing the production lot (order) sequence by swapping elements of the vector determining the order release times
- shifting the operation time windows for each machine by shifting pairs of start/stop times within the vectors containing the machine operating times
- contracting the operation time windows of the machines by a point mutation of start/stop times (delay start & bring forward stop)
- changing the order release times by randomly mutating elements of the order release time vector
- gradually decreasing the intensity of the stochastic changes described above – changing between one and four vector elements at the start and only one towards the end of the optimization run, while generally restricting all changes of time windows to below 25% – this is meant to explore a wider variety of solutions ("global search") at the beginning and conduct a more refined search ("local search") towards the end

Integrating a **memory function** was another means of reducing the optimization runtime, by preventing the optimization from re-calculating solutions that the algorithm has already evaluated once before. This function is an integral part of the Tabu Search algorithm, an optimization heuristic in its own right. In this case we have integrated the memory function within the GA based optimization procedure.

The **mixed integer optimization** is a means of further reducing the search space by restricting the step size for the abovementioned vector changes. In a series of test runs with modulated step size, ranging between 1 and 3600 seconds, steps of 60 seconds proved to be the optimal step size for the given test case. For this test case the effect of restricting the step size was still only moderate but we expect it to be more important in larger models for more complex real-life factories. The same is true for **hybridization,** by combining the GA with a subsequent PS: The improvements in this test case have been minor – it remains to be seen, whether this positive effect grows with an increasing size of the simulation model.

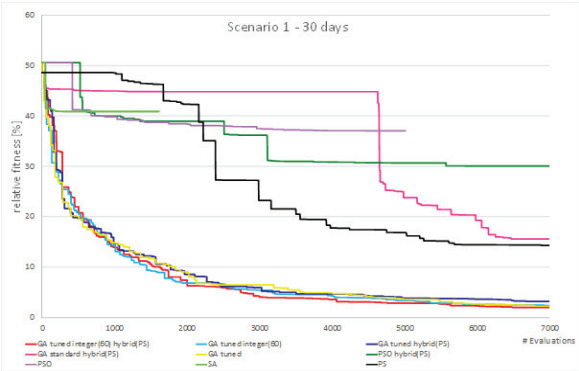

Fig. 4. performance comparison of heuristics – phase 2.

Since the goal function contains multiple criteria, it was important to observe, whether the optimization was able to work with and improve all part-goals.

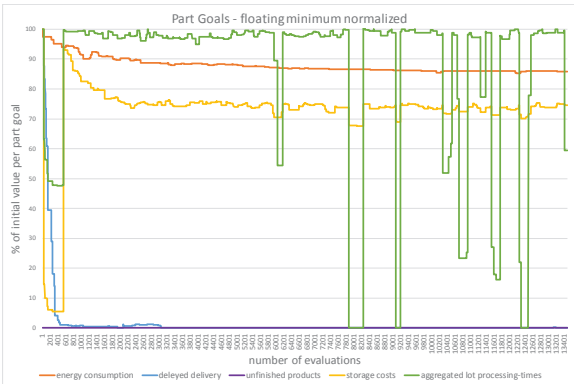

Fig. 5. Part goals during phase 2 – tuned GA.

Fig. 5 shows the part goals trend during the optimization run. The major development is the quickly lowered delayed delivery value (big weight), the slow but consistent reduction of the energy value and the changing balance between the storage costs and the lead times per production lot. The unfinished products value is kept at zero at all times due to its big weight in the objective function.

The last major tuning step for the GA are tests with **modulated population sizes**. With multiple solutions simultaneously being optimized, the GA is especially robust against getting stuck in local optima and stochastic fluctuations – as seen with the results of PS. However, multiple solutions in one generation also means more evaluations and potentially an increased runtime of the optimization. Therefore, it is advisable to determine the optimal population size. Thus, the population size in the experiments presented thus far was set at $1/8^{th}$ x n_{vars} (with n_{vars} representing the number of variables in an optimization scenario). The experimental results showed an increase in optimization speed when lowering the population size until $1/16^{th}$ – beyond that point the stochastic fluctuations increased considerably making the results unreliable.

5.5. Results

The results of this research suggest using a GA with a set of tuning and customization measures for optimal optimization performance. The initial solution used in the optimization tests was based on an actual production plan from the production site this test case was derived from. This manually compiled plan could be improved by (based on the values for the defined objective function):

- 4% by applying the standard GA
- 13% by applying the standard GA in combination with PS
- 32% by applying the tuned GA with mixed integer opt.

Good results are reached within ~2.000 evaluations – with a standard intel-i7 4Ghz processor this would take ~70 minutes to execute. Factoring in slightly more complex (larger and containing more cubes, more variables) simulation models but also a possible parallelization of calculation effort and an ongoing integration of measures containing the search space, we expect to be able to keep the optimization runtime below one hour. A combination of one thorough overnight planning run und subsequent runs during the day, to adapt to changes of conditions, with less complexity, is another possible way to cope with the optimization runtime in practical planning applications in industry settings.

6. Conclusion & Outlook

A suitable integrated planning method for the optimized, energy aware PPC has been developed. Although the optimization thus far was developed with a simplified production line, the basic complexity of the hybrid simulation model is representative of the level of complexity of future applications for the planning tool. The developed optimization algorithm fulfilled the requirements concerning runtime and quality of the solution.

In this ongoing research project, the optimization algorithm will be integrated into the existing simulation module and its software implementation. The next iteration of a simulation prototype will contain the complete model of the production line. This will include a more sophisticated set of TBS and energy system. The basic operating times, scheduling and sequencing representing the variables thus far, will be supplemented with an additional set of variables, and possibly a sub-optimization module, to efficiently optimize the TBS in more detail. Eventually the entire factory and other industry cases will be covered by the planning tool. Finding and formalizing suitable restrictions to reduce the search space will be a key factor for a successful implementation of an optimized PPC method that will be applicable to virtually every kind of production environment.

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