Interdisciplinary multi-criteria optimization using hybrid simulation to pursue energy efficiency through production planning

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ABSTRACT

An energy-efficient production is imperative and can reduce costs. Despite the acknowledged potential to increase energy efficiency in production systems through production planning and control (PPC), adequate planning methods are lacking. This article presents an interdisciplinary approach for a simulation-based multi-criteria optimization, integrating energy efficiency into PPC objectives. The method considers production equipment together with HVAC and technical building services. It features a novel integrated hybrid discrete/continuous simulation method enabling to accurately capture dynamic interactions between material and energy flows. The approach is evaluated in a case study on the food industry, indicating potential energy efficiency gains of up to 30%.

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1. Introduction

Energy efficiency in production is a societal–political necessity [1] and a prerequisite for competitiveness in global markets due to long-term rising costs of energy, with industry accounting for 36% of CO_2 emissions globally [2]. The ongoing energy transition towards renewables adds both the challenge and chances, associated with synchronizing the industry energy demand and volatile energy availability, to the goals of an energy-efficient, sustainable production [3]. For achieving energy efficiency, and especially for mastering the challenges in the wake of the energy transition, the field of production planning and control (PPC) offers significant potential that is currently largely unutilized by companies [4].

Since the lack of available planning methods is one of the major obstacles preventing companies to use PPC to increase their energy efficiency [5], the research presented herein aims at developing a novel planning method enabling to pursue energy efficiency together with traditional economic PPC goals. The resulting method is meant to provide a functionality similar to an advanced planning and scheduling (APS) system that automatically creates a multi-criteria optimized plan. The planning method will not only provide the basic APS functions – compiling optimized detailed production schedules – but also optimize the control of equipment in the periphery of the production process, i.e. HVAC and technical building services.

The most challenging requirement for the method is the necessity to capture, predict energy consumption and manipulate processes within the production system, concerning both the material flow and the thermal–physical behaviour of the energy system. Only with the interactions between both elements considered, can the savings potentials, due to optimal production schedules and optimal operation of equipment, be utilized. The second major requirement is an optimization functionality.

The paper is structured as follows: First, a literature review on the state-of-the art of planning tools is presented and the research gap identified. Next, the two major components of the method are outlined – the simulation and the optimization – combined with an evaluation of the method in a case study. A discussion of the results concludes the paper.

2. State of the art and method concept

2.1. State of the art

This chapter gives a brief overview of existing planning methods and identifies the research gap addressed by this paper. Since the desired planning method is aimed at practically applicable methods, the review of existing approaches is focussed accordingly. The planning approaches can be categorized into traditional approaches, meaning hands-on less sophisticated approaches that have been widely used in industry applications, simulation-based approaches and optimization-program-based approaches.

A good representative for traditional approaches is energy value stream optimization [6] — a technique to systematically optimize production processes in a static, one-time improvement effort. Although potentially affecting PPC, these methods are not able to provide a PPC/APS functionality and the planning principles are too static to be utilized in a dynamic planning method such as an APS.

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Simulation-based approaches try to capture the system behaviour in the form of a simulation model, and near-optimal production plans are compiled through either manual experimentation or simulation-based optimization techniques, in which the simulation serves as an evaluation function. Two approaches stand out as representatives of two sub-groups: Thiede et al. [7] uses a multilevel simulation to model the material flow, production equipment and components of the energy system. Although dynamically coupled, the limited interaction between the models does not allow for detailed consideration of interactions between the energy system and the material flow. The optimization is conducted manually. The second representative is the approach by Rager [8], which contains a simulation-based optimization. It utilizes a discrete event simulation (DES) restricted to the material flow and with deterministic energy consumption. The optimization variables are restricted to traditional sequencing and scheduling and do not include the control of equipment in the periphery of the production process.

The optimization-program-based approaches feature more simplified models of the real life production system in order to be formulated and computable as genuine optimization programs. None of the genuine optimization-program-based approaches can fulfil the requirements concerning a realistic system behaviour.

Table 1 (more details in Ref. [9]) gives an overview of the reviewed approaches, including an evaluation of the degree to which the two major requirements – integrated simulation and automatic optimisation – are fulfilled. Only simulation-based approaches fulfil the model complexity requirement. The two major identified research potentials are: A more comprehensive modelling and simulation of the interactions between material flow and energetic behaviour of the production system, thus enabling accurate and reliable planning results. The second is an optimization module that can cope with the complexity of the model and provide an automatic optimized compilation of production plans and equipment control.

Table 1
Evaluation of existing approaches.

Requirements \ Approaches	Thiede	Junge	Martin	Leobner	Rager	Wohlgemuth	Solding	Heilala	Michaloski	Weinert	Dietmayr	Haag	Rahimifard	Abele	Löfgren	Cannata	Continuous Simulation	Optimization-Based
Modelling of Production System	●	●	◑	◑	○	◑	○	◑	◑	◑	◑	◑	◑	◑	◑	○	○	○
Modelling of Energy System	●	◑	◑	◑	◑	○	◑	●	◑	◑	◑	◑	◑	◑	●	◑	●	○
Interactions between material-flow and thermal-physical	◑	◑	◑	○	○	○	○	◑	◑	◑	◑	◑	○	○	◑	○	◑	○
Automatic Optimization	◑	◑	◑	○	●	○	○	○	○	○	○	◑	◑	○	◑	○	○	●
Readyness for industry use	●	◑	●	◑	◑	◑	◑	◑	◑	◑	◑	◑	◑	◑	○	○	◑	○
Overall fulfilment of requirements	◑	◑	◑	◑	◑	○	○	◑	◑	◑	◑	◑	◑	○	○	○	◑	◑

2.2. Method concept

Fig. 1 gives an overview of the proposed approach: A simulation is utilized as an evaluation function for an optimization module that uses the simulation feedback to create new planning variants in an iterative process. The method is supplied with production data from the company IT (ERP/MES) and will return the optimized plan to the IT for implementation.
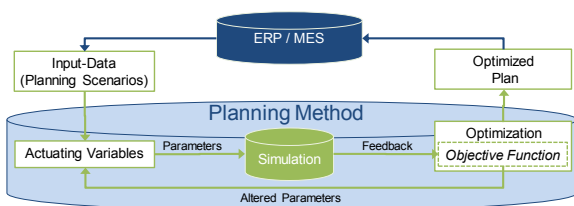
Fig. 1. Basic principle of the developed planning method.

3. Modelling and simulation

3.1. Component-based modelling

For implementing a simulation model of a dynamic system, many approaches and software tools follow a *component-based* paradigm [10] where well-defined model components encapsulate a distinct behaviour and dynamics. These model components are then composed into larger models in a bottom-up manner. Connections between these components represent dependencies and interactions, thereby capturing the dynamic behaviour of the overall system.

One of the advantages of component-based modelling is that it facilitates *separation of concerns*, which makes it easier to manage the complexity of large-scale models and to distribute model development. It also provides modularity and thus enables *reuse* of components by building libraries of validated models that can be instantiated in different contexts, which is crucial in an attempt to reduce the necessary effort for developing new application models [10]. However, in order to retain modularity and composability, it is necessary to encapsulate all aspects of a model component – especially material flow and energetic behaviour – within uniform component boundaries, which we will address in the following section.

3.2. Hybrid simulation

Developing models of production facilities for the purpose of energy efficiency investigations requires incorporating aspects from different engineering domains (production machinery, logistics, energy infrastructure, building) with sufficient accuracy. These aspects usually include descriptions of material flow as well as energy and information flow. While material flow is typically modelled as discrete entities, energy flow – especially its transient behaviour – is more accurately described using continuous (differential) equations. This raises the need for a *hybrid* approach to modelling and simulation that combines discrete as well as continuous simulation models.

Typical hybrid simulation methods employ multi-method *co-simulation* [11,12] that combines different simulation environments (on the application level), e.g. one for the discrete sub-model and one for the continuous sub-model. These sub-models can then be coupled at runtime [13] using some kind of middleware. However, as a limitation, the modeller is forced to split the overall model into different simulation environments along the boundaries of discrete/continuous modelling. In the context of a component-based modelling paradigm, it quickly becomes cumbersome to maintain modular components that incorporate both discrete and continuous behaviour within uniform boundaries, which in turn reduces their reusability. In addition, the computational overhead of co-simulation limits execution speed and thereby the feasibility for simulation-based optimization tasks with possibly thousands of necessary iterations.

In order to be able to design modular, reusable – and hybrid – model components, other directions have to be explored that allow a tighter integration of discrete and continuous models. One possible approach, which we employed in this paper, is based on *hyPDEVS* [14], which is an extended DEVS (discrete event system specification) formalism [15] for hybrid systems. DEVS formalisms are a formal model description, accompanied by an abstract simulator execution algorithm, and allow building models from components in a hierarchical manner by distinguishing between *atomic* and *coupled* components. For more details regarding hyPDEVS we refer to Refs. [14,16].

In contrast to co-simulation, a model description based on hyPDEVS integrates discrete and continuous model aspects on the component level (instead on the application level), thereby allowing to encapsulate material flow and energetic behaviour within the same component boundaries and making it easier develop new hybrid application models by reusing pre-defined components [17].

3.3. Model abstraction

One drawback to using a DEVS-based formalism for modelling and simulation is that DEVS is often difficult to understand for non-simulation experts, thereby hindering potential adoption in industry. In an attempt to improve ease of use for non-expert model developers, we specified a simplified abstraction from DEVS as a *platform-independent* modelling layer (PIM), depicted in Fig. 2.

Based on a first informal conceptual model (CM) of the production facility and its components, the implementation of application models can be done by the user in a platform and simulation system independent manner (in the PIM-layer) based on pre-defined components, called *"Cubes"*.

Afterwards, the Cubes in the PIM can be translated into a hyPDEVS compliant model, either manually (by a DEVS expert software developer) or using automatic transformations. Thereby, a single Cube is translated into one or more hyPDEVS atomics while the Cube layout specifies a hyPDEVS coupling. Besides hyPDEVS, the platform-independent specification of the PIM also allows to translate it into other platform and simulation system specific models, e.g. Modelica or a purely DES.
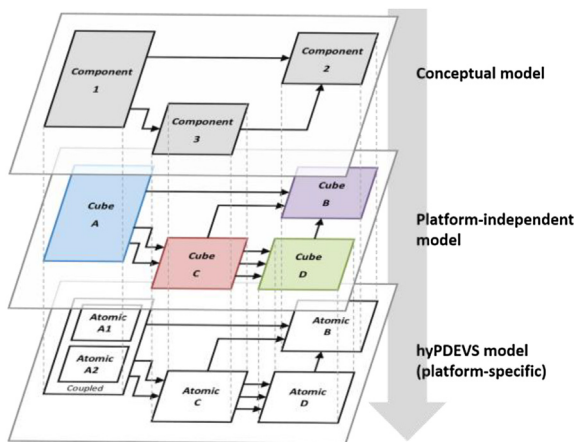

Fig. 2. Different layers of model abstraction: Conceptual model (CM) of the component structure, a derived platform-independent model (PIM), which can be translated into a hyPDEVS-specific model implementation.

3.4. Example Cube: oven

As an example of a Cube, we present a model of a conveyor oven. The oven accepts entities (workpieces, etc.), moves them through a temperature-controlled area and outputs the entities on the other end. Such a conveyor oven can be used for example in an industrial bakery for baking products, or as a hardening oven for treating metal parts. For temperature control, the oven obtains electrical as well as thermal energy, which is converted into waste
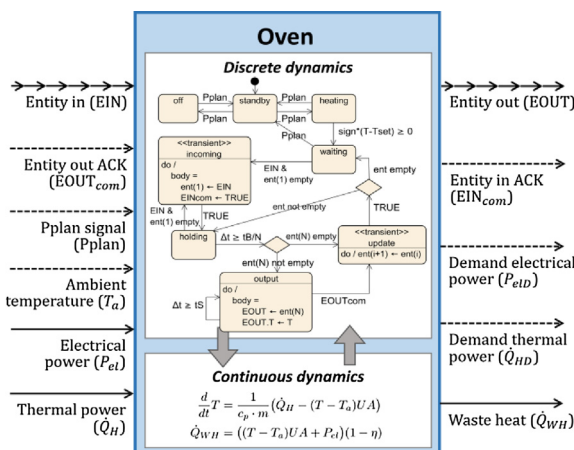

Fig. 3. Oven Cube consisting of a state machine for the material flow (discrete) and differential equations for the energy flow (continuous).
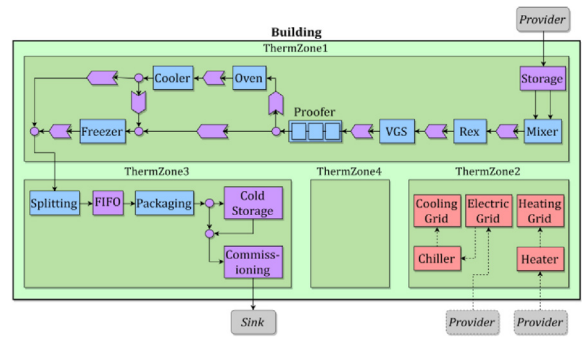

Fig. 4. Structure of the production system model in the case study.

heat. The component is taken from an industrial case study, the corresponding conceptual model is shown in Fig. 4.

Fig. 3 presents an overview of the Cube interfaces as well as internal behaviour. Discrete aspects are specified in the form of a state machine governing the material flow as discrete entities as well as information exchange. For the continuous aspects, energy balance equations model the transient dynamics of the internal temperature. A detailed explanation of the oven Cube as well as a translation of the oven model into hyPDEVS are given in Ref. [18].

4. Optimization and case study evaluation

4.1. Development of the optimization

The complexity of the optimization problem renders it NP-hard, thus necessitating heuristics to achieve good solutions in acceptable time. Since the search space, as a consequence of the number of actuating variables and non-linear correlations, typically features multiple local optima, heuristics with the ability to search for global optima are required [19]. An evaluation showed metaheuristics as the best potential fit for this problem category. The optimization was developed in two stages: First, different metaheuristics were evaluated using identical scenarios of a simplified industry test case. Second, the best performing metaheuristics from phase one were then enhanced and customized to provide an optimal fit for the given optimization task and model behaviour.

A genetic algorithm (GA), with a set of tuning and customization measures for optimal optimization performance, emerged as the best performing solution. More details can be found in Ref. [20]. The customizations comprise: a *guided search* by adapted operators in the GA, a *memory function* from the Tabu Search algorithm, a *mixed integer optimization, hybridization* by combining the GA with Pattern Search and determining the *optimal population size*. Another major adaptation is splitting the optimization procedure into *two phases* — a measure to improve the runtime of the optimization. In the *first phase* only the sequencing and scheduling of orders are enabled. This is followed by a *second phase* with a fixed order sequence, during which the operation time windows for machines and equipment in the periphery are being shifted and contracted, mainly in order to minimize the energy consumption. The last major adaption is the introduction of a *production plan generator* (PPG), the goal of which is to minimize the number of practically infeasible solutions created by the optimization (GA). This in turn decreases the number of necessary simulation evaluations and prevents the GA from "getting lost" in practically infeasible solutions.

4.2. Case study evaluation

The case study is based on a production line for rolls in an industrial bakery in Austria, which is moderately energy intensive and features a complex material flow. The basic model structure is shown in Fig. 4. It consists of nine major production machines, nine conveyor belts with junctions and three storage units, plus HVAC

equipment. The products, baked and deep-frozen rolls, use different material flow paths – mainly with and without passing through an industrial oven – and require different process parameters, e.g. temperatures and processing times on machines.

The objective function (1) for the multi-criteria optimization was parametrized in accordance with the management of the bakery using real life cost and process parameters.

ω_1 - ω_6 ... part-goal weights
n ... total number of production lots
m ... total number of product types
$f_1(c_j)$... evaluation function for late deliveries (based on product types, normalized into cost value)
$f_2(d_i)$... evaluation function for storage costs (based on production lots, normalized into cost value)
$n_2 k_1$... accumulated overall energy costs (including CO_2 penalties, normalized into cost value)
n_3... unsatisfied production demand (normalized into cost value)
n_4... production equipment utilization (opportunity costs for prevented additional production volume)
n_5... accumulated lot changeover-costs (normalized into cost value)

The results of one representative scenario (see Fig. 5) show an overall improvement of 45% compared to a manual planning solution. This includes lowering penalties for late deliveries. The overall energy costs – including CO_2 emission costs – dropped by 21% (others scenarios up to 30%). The scenarios featuring variable electric energy costs (spot market prices), showed an increased optimization potential, with the biggest gains in summer scenarios. This is due to the larger cooling demand in the summer plus the greater availability of relatively cheaper renewable, solar-based, energy.
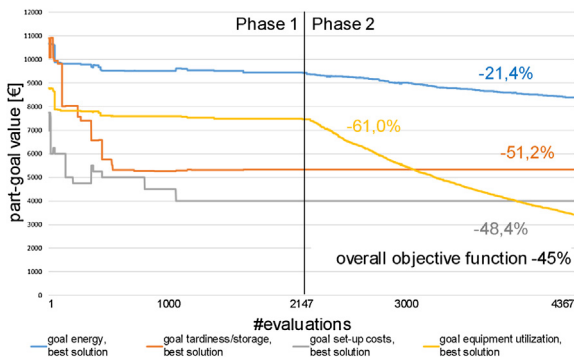

Fig. 5. Case study results (example scenario): Part goal trends during the optimization run for a 7-day scenario in the summer.

5. Conclusion and outlook

The method is able to provide a functionality similar to an energy-aware APS and it represents a significant development step from existing methods: The hybrid simulation enables accurate prediction of energy demand in different scenarios, thus allowing to pursue energy efficiency through planning. At the same time, the abstraction and reuse of model components simplifies the task of developing new application models.

Together with the developed multi-criteria optimization, the management can pursue a complex goal-set with their PPC. The dynamic nature of the planning method allows for the integration of current energy market data, thus potentially supporting a sophisticated energy portfolio management. The case study evaluations showed the method to be successfully applicable to real life applications and their associated planning complexity.

However, there are potential challenges for a live application of the method: First, model development still requires significant effort and expert domain knowledge as choosing the adequate model detail is imperative. Second, calculation performance is

critical – the "affordable" number of simulation evaluations is near the minimum for a GA to work properly – making it necessary to include empirical knowledge about the production system into the optimization algorithm.

Acknowledgement

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