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Hybrid simulation-based optimization of discrete parts manufacturing to increase energy efficiency and productivity

Thomas Sobottka[ab]*, Felix Kamhuber[ab], Matthias Rössler[c], Wilfried Sihn[ab]

[a]*Fraunhofer Austria Research GmbH, Theresianumgasse 7, Vienna 1040; Austria*
[b]*Vienna University of Technology, Theresianumgasse 27, Vienna 1040; Austria*
[c]*dwh GmbH, Simulation Services, Neustiftgasse 57-59, Vienna 1070; Austria*

* Corresponding author. Tel.: +43-676-888-61626; *E-mail address:* thomas.sobottka@fraunhofer.at

Abstract

This presented research comprises the development of an optimization module for use in a novel production optimization tool – similar in function but not mode of operation to an Advanced Planning System –, with energy efficiency incorporated into its goal system. The optimization features a hybrid-simulation of production systems as an evaluation function. A hybrid simulation has been developed and presented in preceding publications, in order to enable a sufficient consideration of interactions between material flow and the thermal-physical behavior of the production system. The size of the search space for the complex optimization problem necessitates a customized two-phase-optimization method, which is based on a Genetic Algorithm, with the consideration of linear constraints and extended customizations. The results, obtained in a case study featuring a food production facility, show energy savings of around 20 percent together with significant productivity gains.

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Keywords: sustainable manufacturing; energy efficiency; production planning; optimization; metaheuristics; hybrid simulation; case study

1. Introduction

Human contribution to climate change necessitates urgent action: In the United Nations Framework Convention on Climate Change (UNFCCC) [1] countries worldwide have committed to limiting the manmade temperature rise to 2°C, mainly by reducing energy related CO_2 emissions by 1.9% between 2013 and 2040. The increased awareness and societal pressure for increased sustainability, together with long-term trends of rising energy costs and the fact that the industrial sector is responsible for 31% of the annual energy demand and 36% of the CO_2 emissions globally [2], are turning energy efficiency into a substantial goal for manufacturing enterprises

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[3]. 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 [4].

In addition to the need to be more energy efficient, there are also chances for companies in the domain of energy efficiency and sustainable manufacturing: The ongoing energy transition towards renewable energy sources leads to a more volatile energy supply. The larger the share of renewable energy in the supply mix, the better the demand has to be aligned with the energy production – bidirectional approaches such as demand response are one way of achieving this [5]. This also means that if companies can predict, plan and control their energy consumption profile according to changing supply situations, they can benefit from very low energy prices on short-term energy markets.

Both goals, increasing energy efficiency and the ability to plan and control the energy consumption profile, necessitate advanced planning tools for companies, especially for manufacturing companies with complex productions systems. Studies show that energy efficiency considerations should be an integral part of Enterprise-Resource-Planning (ERP) and Manufacturing Execution Systems (MES), with simulation based approaches suggested to be the most promising method. However, currently there is a lack of practically applicable planning methods [6].

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. The general planning concept has been published by the research team [7], so has the hybrid simulation concept [8] and the development of the optimization module [9]. The particular paper at hand focuses on the adaption of the planning method to a specific real life industrial application and on evaluating the optimization potential in an industrial use case.

2. Requirements for the Planning Tool and chosen Approach

The **requirements** for a planning tool have been deducted from an analysis of relevant literature, supplemented by expert interviews with managers from 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 [10]. Li [11] stresses the necessity for a generalized 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 [12]. An automatic decision support function, i.e. in the form of an optimization module, is another major request from prospective industry users. A classic decision support function for production planning and control in company Information and communications technology (ICT) is found in Advanced Planning Systems (APS).

Following a comprehensive evaluation of possible **approaches** for this research, a simulation based optimization emerged as the most suitable option: It enables a planning functionality similar to that of an APS, due to the automatic optimization of production schedules and control of machines in the production process and the periphery. It also enables the simultaneous consideration of the complex system of material flows and the thermal-physical behavior of the production and energy system and its components through a simulation of said production system.

3. Related Work

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 [13]. Typically, material flows and the processing of orders are simulated utilizing a discrete event simulation (DES), while the thermal-physical behavior of machines and equipment is usually simulated in continuous simulation environments that solve ordinary differential equations (ODEs) or differential-algebraic equations (DAEs). One of the most advanced simulation based concepts for planning tools in the field of energy aware planning is Thiede's approach [14] based on AnyLogic® in a multilevel-simulation [15, 16]. 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. In order to ensure the cooperation of different model parts in a co-simulation, the respective solvers of the subsystems have to be synchronized. This generates various iterations and overhead, especially for solvers with a variable step size, which are commonly used in continuous simulation environments. As the focus of this research is more on the continuous part than Thiede's work, a co-simulation approach is not feasible and an integrated hybrid simulation was chosen and developed, enabling the modeling of 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 [17]. 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 [18]. The metaheuristics can be discerned in algorithms based on iterative local search (LS) and generative population based methods (PS) [19]. Most of these heuristics mimic natural processes, i.e. imitating animal behavior, evolution in biology or the cooling process 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 [20]. Due to the increased model complexity in the case of energy aware planning, there are examples of approaches based on the Genetic Algorithm (GA) [21]. Rager [22] utilizes 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 and supports the more complex hybrid simulation developed and used in this research, thus a customized optimization method has to be developed.

4. Hybrid Simulation

In order to be used within the proposed planning tool the simulation has to fulfil three major requirements:

- *Support for hybrid models:* The combination of logistics simulation, which is typically simulated using a discrete event simulation (DES), and the simulation of the energy flows, that is continuous in nature and are therefore modelled as ordinary differential equations (ODEs) or differential algebraic equations (DAEs). This combination is not supported by current planning tools and thus is the main innovation of the proposed software tool.
- *Modular structure of models:* For the use in a wide variety of settings, the models for the simulation should feature a modular structure. This enables the development of a library of basic components of production facilities (such as belts, ovens, manufacturing equipment, HVAC-systems, thermal zones) that can be used to build the model of the facility and that can be used for the simulation.
- *Description in one formalism:* The integration of the simulation in an existing MES/APS can be realized by either connecting to an existing, external system or implementing the simulation environment in the program itself. For this project the second method was chosen. As mentioned before, the usage of a co-simulation approach is not feasible for the focus of this research. Thus, the models have to be described in one formalism in order to keep the effort for development and implementation of the simulation engine as low as possible.

In order to fulfill these requirements the DEV&DESS-formalism in combination with PDEVS was chosen to describe the hybrid models – in the context of this research the approach was called "Hybrid P-DEVS". For testing purposes and first implementations the MATLAB-DEVS-Toolbox developed by HS Wismar [23] was used. For the purpose of the optimization, the performance of the simulation had to be tweaked, so a software implementation partner implemented the engine in C++ [8].

5. Optimization Module

The optimization module that utilizes the hybrid simulation as an evaluation function was developed in two phases: First, different metaheuristics that are suitable for complex multimodal (featuring local optima) fitness-landscapes were evaluated using identical scenarios. Second, the best performing heuristics from phase one were then enhanced and customized to provide an optimal fit for the given optimization task and model behavior.

At the end of the development process, a Genetic Algorithm (GA), with a set of tuning and customization measures for optimal optimization performance, emerged as the best performing solution. In a simplified test case, the optimization was able to improve the objective function of the optimization by up to 30%. More details by the same authors concerning the optimization module have been published [9].

6. Potential Analysis in a Case Study

6.1. Case-Study Setup

For this Case Study, the simulation of an actual production line for rolls in an industrial bakery plant was chosen as the production system. It consists of nine major production machines, nine conveyor belts with junctions and two storage components within the production logistics system. The products, baked and deep-frozen rolls, use different material flow variants – mainly with and without passing through an industrial oven – and require different process parameters, e.g. temperatures and processing times on machines. These product characteristics are stored on and used as input via process sheets. Two of the production machines – an industrial oven and a freezer – feature a distinct thermal-physical behaviour. The basic model structure is depicted in Fig. 1.

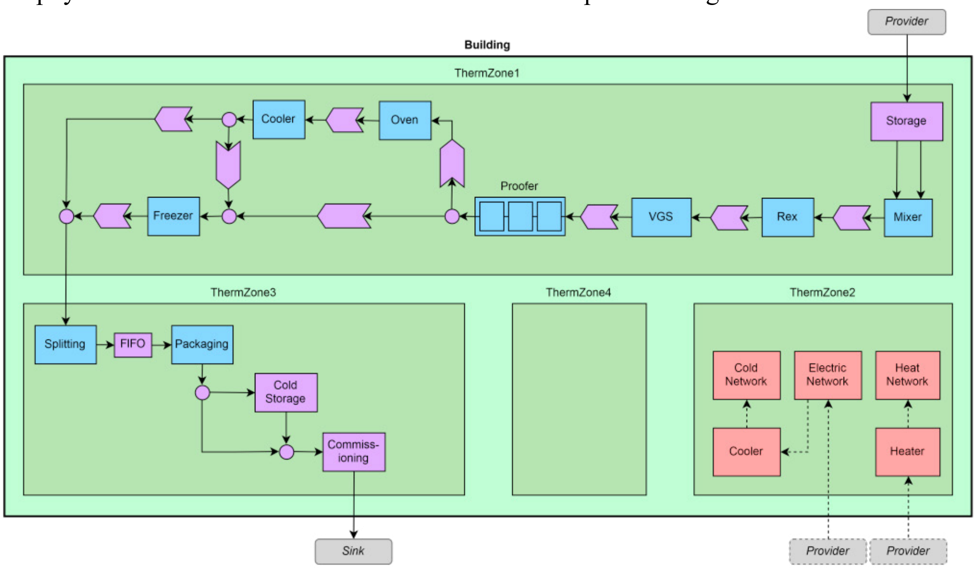

Fig. 1. Simulation model: structure plus material and energy flows

In the Technical Building Services (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. Next to the heat network, there are three cold networks and one electric network. The cold networks contain five chillers. The external environment is considered by importing weather data – i.e. temperature, wind and cloud coverage. Scenarios for three seasons in 2016 have been tested (seasons following the weeks 03/34/44). In the simulation model, 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 hybrid simulation is implemented in a C++ software and the optimization is implemented in Matlab® using the Global Optimization Toolbox. The simulation model was parametrized with actual data from production, process and comprehensive energy measurements conducted in the production plant.

The production scenarios presented in this paper feature 1-day-/7-day-scenarios (simulated time) and feature all 12 product types that are produced on the production line. The imported production/demand schedules are actual production schedules from the fall of 2016. The base planning is the actual production schedule created by manual planners that was executed in the past against which the optimization results are now being evaluated.

Concerning the multi-criteria objective function for the optimization, the basic function developed in [9] was adapted – i.e. parametrized and weights assigned to the part objectives – in the course of goal-system workshops with the planners and management of the bakery. The following function emerged:

$$f(x) = \omega_1 \sum_{i=1}^{n}(f_1(c_i)) + \omega_2 n_2 k_1 + \omega_3 n_3 + \omega_4 n_4 \tag{1}$$

ω_1 - ω_4 ... 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 overall energy costs
k_1… overall energy cost per kWh
n_3… number of unfinished goods (demanded goods not produced)
n_4… number of unfinished goods (goods not produced)

The objective function is normalized to calculate a cost value denominated in Euro. The part-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. The second part considers the energy consumption – the overall energy costs are calculated as a combination of the actual energy cost per energy source and a cost value for the associated CO_2 emissions. For the actual electric energy costs, a number of scenarios have been tested: Season 0 features the current fixed price for the bakery, whereas scenarios with seasons 1/2/3 use the actual spot-market prices for electricity in the winter/summer/autumn of 2016 (seasons following the weeks 03/34/44) [24]. Thus, in the latter three scenarios the opportunities of a complex energy-portfolio-management utilizing the short-term markets are evaluated. The energy cost for cooling is calculated using the consumption data of the electrically powered coolers. For the heat production the actual costs for the company was used. Concerning the cost value for the associated CO_2 emissions, the energy usage per energy source was combined with corresponding conversion rates for Austria [25], evaluated with Spot-market prices of the European Energy Exchange AG [26] and an additional value, which the management of the bakery assigned to reducing CO_2 emissions. The third part of the objective function evaluates penalty costs for unsatisfied demand during the simulation and the fourth penalizes unfinished goods at the end of the simulation.

6.2. Adaptations to the Optimization Module

The optimization module developed in [9] has been adapted for the complex production system of the case study. The major components of the optimization, a customized/tuned Genetic Algorithm (GA) remain unchanged. The customizations comprise: a **guided search** by adapted operators in the GA, a **memory function** from the Tabu Search algorithm, a **mixed integer optimization** (default value 1)**, hybridization** by combining the GA with the PS and determining the **optimal population size** (the population size was set to 12).

The most prominent adaptation of this basic optimization is the separation of the optimization procedure into two phases – this is a measure to improve the runtime of the optimization. Due to the large search space created by real life production systems, it proved beneficial to only enable the sequencing and scheduling of orders in the **first phase**. 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. It is important to note however, that although the actuation variables of the optimizations change, the simulation is always considering the entire production and energy system. Thus, in both phases the entire objective function can be optimized, including the energy consumption. The new approach requires adaptations in the constraints in both phases. In the first phase, the only necessary constraint is to have positive order release times. In the second phase, overlapping processing on any given machine has to be prevented as well as ensuring the operating times on every machine are at least as long as the minimum processing time for each production lot on the same machine.

A second 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 significantly decreases the number of necessary, computation-intensive, simulation evaluations and prevents the GA from "getting lost" in search space areas without practically – according to the objective function – permissible solutions. The PPG accesses the process sheets and, based on received order release times, calculates production plans for each machine and piece of equipment. The PPG significantly increases the optimization speed and quality of the results. In phase 1 the PPG is called after every simulation run for every intermediate solution. Between phases 1 and 2 it is called again to ensure feasible oven operating times and ensuring the linear constraints are not violated. In phase 2 the PPG also receives optimized oven times for every intermediate solution to calculate the operating times of the remaining equipment. Given the current simulation performance and the complexity of most real life optimization tasks with this planning method, the use of a PPG is likely to be necessary for most applications. The downside is that it has to be adapted to the specific simulation model and thus increases the modelling effort – a fact that the research team is currently trying to mitigate developing a generalised and modularised approach, including the PPG.

6.3. Case-Study Results

Although scenarios with 1/7/30 days simulated time have been conducted, the most usable anticipated application case right now is the one day planning horizon, thus the presentation of results will focus on the one day scenarios. Fig. 2, (a) shows the influence of different seasons and corresponding weather conditions and electrical energy prices (spot-market) on the optimization potential. Fig. 2, (b) shows the part goal trends during the course of the optimization by displaying the mean values for each generation of a GA population. The latter diagram shows the trade-off between the part goals in the objective function and that in phase 2, after a significant improvement in overall energy costs, the optimization soon reaches a point where no significant improvement is achievable for any part goal, without creating solutions with unfinished products. Increasing the optimization step-size – a measure to reduce the possible solution space size – from 1 seconds to 300 seconds improves both optimization speed and solution quality (see Fig. 3, (a)). It is important to adjust the constraint tolerances to the chosen step size.

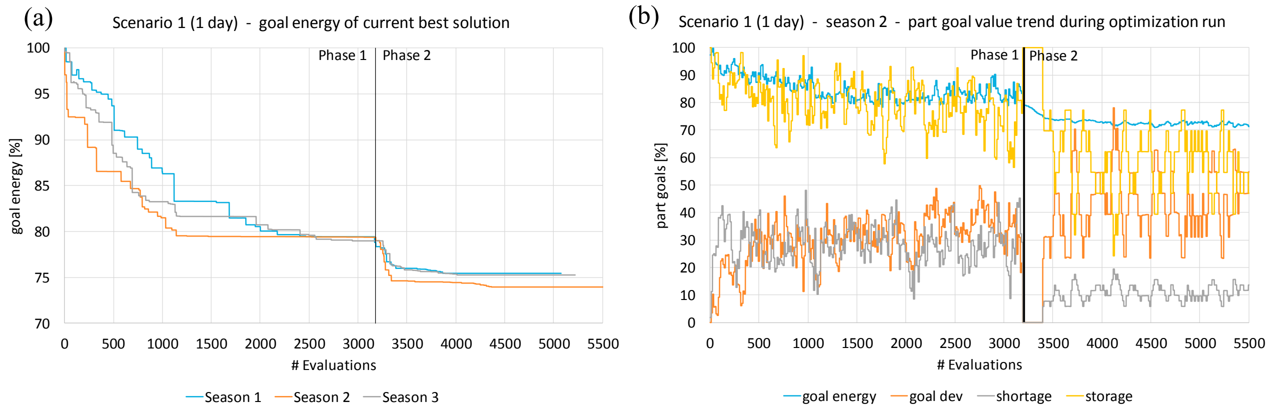

Fig. 2. (a) energy goal trend of current best solution; (b) part goal trends of mean values per generation

The overall optimization, in terms of a reduction of the objective function value, in the one-day scenarios was around 50%. This includes lowering penalties for late deliveries, which are a common occurrence in the manual planning process. The energy consumption could be lowered by 33%, while the associated overall energy costs – including CO_2 emission costs – dropped by 25%. The scenarios using variable electric energy costs (spot market prices), showed an increased optimization potential, with the biggest gains in week 34 (summer scenario). This is due to the larger cooling demand in the summer plus the greater availability of relatively cheaper renewable, solar-based, energy. The results could be obtained in ~4.400 simulation evaluations and as many intermediate solutions (with default settings). In the result trends, it is apparent that the number of evaluations to achieve good results could be reduced to ~2.300 evaluations by shifting the phase transition point to around 2.000 evaluations. On a standard intel-i7, 4 GHz processor 2.300 simulation evaluations take ~3 hours to execute.

Longer scenarios have been conducted although there are practical limitations: The complexity of seven-day scenarios, in terms of search space size, is ~300 times larger than that of the one-day scenarios. Given the practical requirements for an optimization to be executed in not more than 2-3 hours in order to be able to utilize the planning results, this results in a too small number of possible evaluations to achieve good results, compared to the theoretical optimization potential. By further reducing the population size, the optimization speed can be significantly increased, however this also leads to less reliable results – one of the major advantages of population based metaheuristics is the simultaneous optimization of a large population of intermediate solutions (see Fig. 3, (b)).

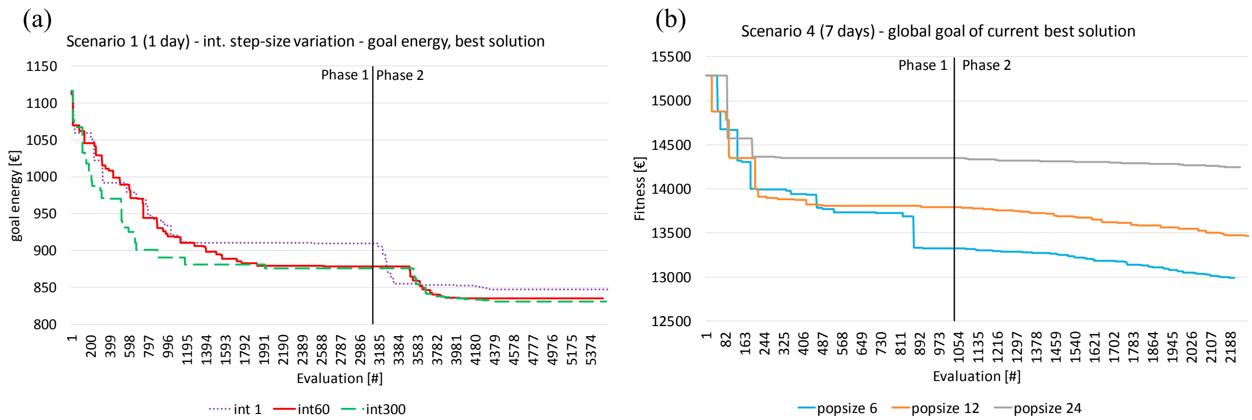

Fig. 3. (a) influence of varying optimization step sizes; (b) varying GA population sizes for 7-day scenario

In the next iteration, the optimization module will also be included into the software implementation that already contains the hybrid simulation. This is expected to significantly improve the overall planning process performance. With this implementation, the simulation evaluations can be conducted simultaneously, which, together with common multi-core processors, has the potential to further increase the optimization speed.

7. Conclusions and Outlook

The research presented herein is able to demonstrate that the planning method for the optimized, energy aware PPC, developed in the course of the research project, is applicable to the planning of real-life production systems. A number of adaptations within the optimization module were developed in order to cope with the complexity and specific requirements of the investigated case, while the simulation modelling was possible by relying on the already developed simulation modules. The results show significant overall optimization potential of up to 50% of the objective function value, including a reduction of ~30% in the energy consumption. When considering variable energy prices on spot-markets, the energy-related optimization potential increases. It is important to state that the optimization potential is very much dependent on specific scenarios – in the majority of the scenarios tested thus far, the overall potential varied between 15-50%, with the overall energy cost optimization of 8-25%. It also has to be noted that optimizing the operation time windows of production equipment potentially introduces risk into the production system. Before implementing schedules created with the planning method, it is therefore advisable to check the generated plans for feasibility; including safety margins to the operation time windows is another possible measure to mitigate potential risks. The simulation of stochastically distributed risk is not feasible since it would greatly increase the number of necessary simulation runs, which are already the major limiting factor for the application of this planning method. The next steps will include a more sophisticated planning for the TBS part of the production system. While already being simulated with the current tool, the next iteration will include actuating variables for the TBS, such as a prioritization of multiple devices in one supply network – i.e. coolers – or setting the target temperature in heat reservoirs and circuits. This will further increase the overall optimization potential and introduce more complexity for the optimization task. In a final step, the planning method will be applied to improving entire factories with multiple production groups/lines/plants.

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