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Combining material flow simulation and optimization for sustainable manufacturing – application in automotive paint shops

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Abstract

The necessity for sophisticated decision support in industrial manufacturing has been described manifoldly and simulation approaches as well as optimization methods are continuously developed. This can be especially promising when it comes to decision-making with multidimensional requirements of economic and ecological efficiency. However, due to the required expert knowledge, there is still a gap between theoretically applicable and industrially applied methods. The paper therefore presents results of two use cases as part of the European project ECOFACT where different approaches for the combination of simulation and (heuristic) optimization were applied with industry partners. An overview of recent works and systematic literature reviews of sustainable manufacturing and the approaches for combining simulation and optimization is given. Correspondingly, the investigated use cases of automobile paint shops refer to the reduction of environmental impacts by optimized heating processes and an improved batching process to minimize paint waste. In the first case, setup times for heating color pools and ovens were shifted to avoid load peaks in a calculation time of less than one minute. In the second use case batch size was increased by around 25%.

Keywords: Sustainable manufacturing; Energy; Simulation; Optimization

1. Introduction

Sustainability has become a fundamental and non-negotiable requirement for societal and industrial development. Not only do the UN Sustainable Development Goals of 2015 serve as an overarching guideline in politics and business, but government regulations are also becoming increasingly relevant to industrial operations. For example, the newly published European Sustainability Reporting Standards (ESRS) [1], which implement the 2022 published Corporate Sustainability Reporting Directive (CSRD) [2] require a much larger proportion of European companies to report on the environmental and social impacts of their industrial practices, and vice versa. Thus, decisions in (industrial) manufacturing need to incorporate sustainability goals and metrics. The H2020-funded European project ECOFACT contributes to this. Overall, it will provide a decision support platform for more environmentally friendly manufacturing systems. As a part of the platform, optimization and simulation models have been developed for improved multi-criteria decision-making in discrete manufacturing. Two specific models for selected use cases in automobile manufacturing have been built and will be presented in the following. So firstly, a brief overview on applied models for sustainable manufacturing is shown in the following. Then, a systematic overview on approaches to combine optimization and simulation is provided and serves as a theoretical basis for the description of the use cases in section 4. The paper concludes with a summarizing result overview and an insight into challenges for the implementation as well as an outlook on next possible development steps from both a research and an industrial perspective.

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2. State of the art

2.1. Considering sustainability in simulation and optimization

Back in 1993 Alting et al. [3] described the Life Cycle Concept as a backbone for Sustainable Industrial Production. Besides the elaboration of product design requirements, several key development issues for sustainability improvements of the production environment were presented. Two of them comprise assessment methods for environmental issues and the integration of information technology into industrial decisions. Since then, the proposed approaches have constantly grown.

Material Flow Simulation (modeled as a sequence of discrete events) is seen as one established method for the analysis and forecast of production system behavior (see e.g. VDI 4499 [4]). Following a literature review by Wenzel et al. the additional consideration of energy as an input factor and target criteria gained relevance since 2011 [5]. Basically, this leads to the combination of two different flow systems with distinct characteristics. Production processes (also in the latter described use cases) can be represented as discrete steps, whereas the energy flow is continuous and requires discretization to be simulated in the same environment. Among several goals, peak shaving and the reduction of load peaks as well as scheduling under energy-related restrictions were identified. The corresponding indicators incorporate energy consumption evaluation with a wide variety of reference values (e.g. energy consumption per batch, over time or per system element). The detail for modeling ranges from single machine operating states up to whole plants and buildings. This flexibility leads to a large set of observable questions and use cases but also requires systematic approaches and thoughtful modeling, analysis and interpretation. As elaborated by Köberlein et al. [6] several pitfalls ought to be considered and overcome to generate meaningful results in simulation studies. This is accounts for both, simulation projects with and without energy-related information. Concerning ecological sustainability in a broader definition, several works for integrating environmental assessments and simulation have been proposed. As an example, Rödger et al. [7] describe an approach for merging Life Cycle Assessment (LCA) and manufacturing system simulation. It addresses the shortcomings of traditional LCA, such as its static character and inability to consider the dynamic effects of time-dependent variables. By integrating manufacturing system simulation, the approach can assess dynamic effects in manufacturing systems on resulting life cycle impacts from both the product and the production system. Further research works that try to tackle the combination of simulation and optimization had already been developed, for example:

- Brondi and Carpanzano [8], who propose a modular and simulation-based method for calculating the environmental profiles of a production line,
- Sproedt [9] developed a decision-support tool that assesses eco-efficiency of production systems based on discrete event simulation,
- Pirola et al. [10] who apply a discrete-event simulation model for sustainable production scheduling in the textile industry.

The latter serves as an appropriate bridge to the relationship between simulation and optimization. Simulation acts as a digital representation that reflects the complex processes of real production. It provides a platform to evaluate random events such as machine downtime or turbulence in station cycle times. In addition, the simulation captures the interaction of control logics between subsystems in production and shows how they work together and affect the production process dynamically.

In contrast to this, optimization steps in to turn these insights into actionable solutions. Optimization approaches in production scheduling aim to maximize or minimize defined goals by matching a set of required tasks with available machines and operations. Based on the established notation triplet by Graham et al. [11] scheduling problems are classified regarding:

- their machine environment (e.g. flow shop, open shop)
- the job characteristics (precedence, permutation etc.)
- the objective (e.g. makespan, weighted tardiness)

The problems encountered in manufacturing are often defined as NP-hard problems due to their complexity, multiple constraints, objectives, and thus large solution space. NP-hardness is a classification of the complexity for such kind of problems that are not solvable in polynomial time. Finding optimal solutions may require significant (or even infeasible amount of) computational resources to find the optimal solution, which can be very challenging in practice. In response, heuristic and approximate algorithms, which can provide adequate solutions in a short time for practical applications, have been developed. For example, in a recent literature review Jiang et al. [12] examine which type of solution approaches are applied for the job shop scheduling problems. Therefore, methods are classified into exact, heuristic, and meta-heuristic approaches of which the latter ones are the most often used. Similarly, Neufeld et al. [13] elaborated in a recent systematic review that metaheuristics are also predominantly used to solve multi-objective hybrid flow shop problems. This modeling approach is another subtype of scheduling problems, with more similar characteristics to the subsequently introduced use case.

Similar to the described sustainability extension of simulation, research on scheduling problems has been investigated regarding the expandability towards environmental criteria. A broad overview of sustainability indicators in scheduling is provided by Akbar et al. [14]. Furthermore, the combination of scheduling and further optimization issues has been investigated. For instance, Vaez et al. [15] describe a combined method for lot-sizing and scheduling under sustainability considerations. Numerous works were published regarding energy-aware, energy-efficient or energy-flexible scheduling operations. Based on it, a variety of literature reviews is available (see e.g. [16–18]). In many cases, the developed approaches aim for the reduction of load peaks or power balancing to maximize the utilization of renewable energy by optimizing production performance simultaneously.

2.2. Approaches for combining optimization and simulation

Considering the complexity and stochasticity of real planning problems, heuristic but also exact optimization methods can lead to a severe simplification and potentially miss important details or relationships. The combined application of simulation and optimization may help production managers and engineers to better understand their production process and identify the cause of problems, as well as to predict system behavior for "what-if" scenario and line performance for future production programs. The goal of coupling a simulation model with an optimization procedure is to adequately solve complex problems and combine benefits of both domains. According to März and Krug [19] these hierarchical or sequential setups lead to 4 different coupling methods (see Figure 1):

1. Optimization-integrated simulation: simulation is the leading system und optimization solves a problem based on a temporary simulation status.
2. Simulation-based optimization: simulation is started based on optimization results and provides dynamic forecasting for further optimization cycles.
3. The simulation results as the initial value of optimization: Simulation is firstly completed and results are provided to the optimization.
4. Simulation evaluates the optimization: Simulation is applied to check feasibility of the optimization.

The second case is also called simheuristics, when any type of (meta-)heuristic algorithm is applied [20]. In this case, simulation is here to evaluate each (or selected) solutions found by the heuristics-component. Especially approach 4 gained relevance in the investigation of energy-aware scheduling (see e.g. [21, 22])

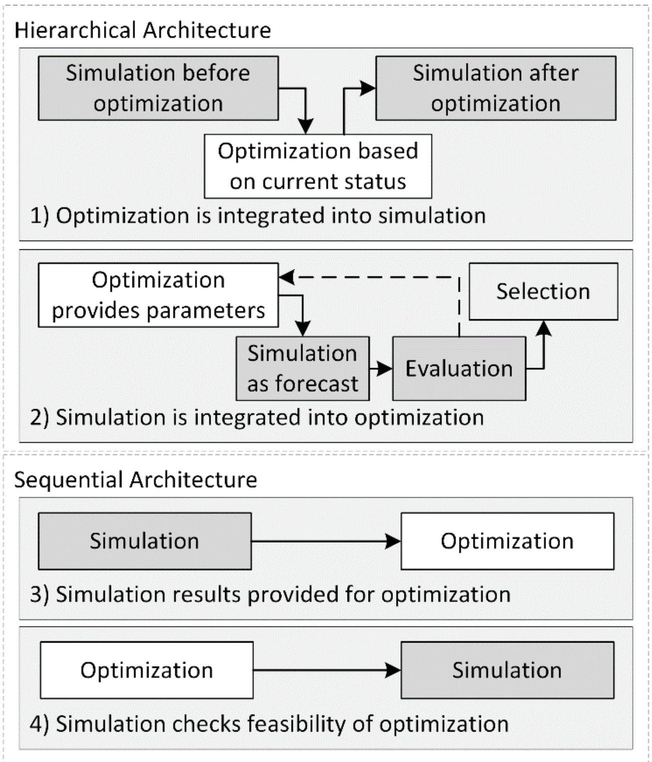

Figure 1: Methods for coupling simulation & optimization

3. Specific use cases of automotive paint shops

In the ECOFACT project the automotive plant of Tofaş Türk Otomobil Fabrikası produces both passenger cars and commercial vehicles. In the paint shop, the cars undergo a multi-step painting process that includes the application of E-coat, primer, and top coat, with each layer contributing to the car's aesthetics, rust protection, and overall durability. Two use case studies were conducted for this plant: one using simulation-based optimization to reduce load peaks for preheating ovens, and the other using simulation to evaluate optimization results for optimized batch sizing.

3.1. Simulation-based optimization for start-up times

This use case focuses on enhancing decision-making for the optimal start-up time for the so-called E-Coat line. The E-Coat line is a vital part of the paint shop and consists of two separate paint lines designed for various vehicle models. Each line has two parallel pools for coating and two parallel ovens for heating. After the heating process, cars from both paint lines merge and proceed to the shared Sealing line. Additionally, there are reserve areas both before and after each E-Coat line, where car bodies can be buffered.

Each morning before production begins, the tanks and ovens must be heated. However, maintaining the required oven and bath temperatures consumes a significant amount of energy. Therefore, it's important to start the heating process as late as possible, while ensuring timely preheating of the pool and oven, which is critical to the efficiency of the subsequent sealing process. Currently, the start-up time is determined manually, based on the experience of the line operators. Each of the two lines is controlled independently, without taking into account the reserve levels of the other E-Coat line. This approach often results in premature start-up, which can lead to unnecessary energy consumption. Figure 2 shows the architecture of the simulated and optimized system. The model includes two E-Coat lines and their connections to the body shop and sealing line. Each E-coat line includes three reserve areas, a pool and two ovens. They converge at the end of the last reserve areas and enter the sealing line. The capacity of each section, the length of the production line, and the production speed have been calibrated to match actual production. The goal of this use case application, using the simheuristics method, is to:

1. Investigate how the fill levels in the reserve areas affect the optimal startup time for both production lines.
2. Provide quantitative recommendations for improved startup times.

To efficiently simulate the E-Coat line, the processing stations in the pool such as degreasing, rinsing, activation, phosphating, cataphoresis and others are simplified in the model as they do not have a significant impact on the research questions. All subprocesses in the tank and furnace are considered as a whole, with a total capacity and processing time, and are represented by the use of conveyors. The parameters for these conveyors, such as transport length, speed, and car body spacing, are based on real-world conditions.

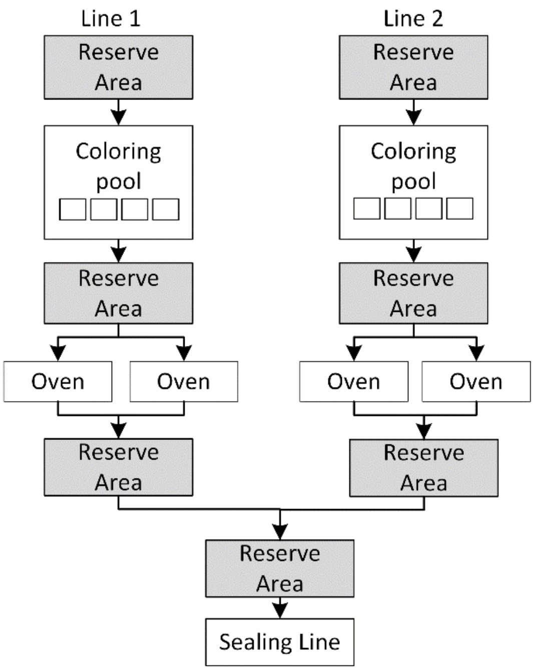

Figure 2: Schematic representation of the E-Coat Line

There are several assumptions that need to be considered. In the absence of specific data on energy consumption and heat-up times as a function of equipment and ambient temperatures, it is assumed that uniform energy and time are required for each heat-up and that the equipment will consume a constant amount of energy to maintain the temperature. Based on this assumption, the last possible heat-up time is chosen to reduce the total run time of the heating equipment, resulting in the most energy efficient solution. The model's simplifications and assumptions aim to balance accuracy and feasibility, while producing practical and useful results.

To ensure accurate results, this simulation includes a number of input and adjustable parameters that are implemented at the beginning of the simulation to simulate the initial state of the line left over from the previous day's production, including:

- initial fill levels per area,
- production rates per line
- pre-heating times per pool (optional)
- pre-heating times per oven (optional)
- energy to maintain temperature in pools (optional)
- energy to maintain temperature in ovens (optional)
- shift start time (optional)
- reserve area capacity (adjustable)
- pool and oven length (adjustable)
- pool and oven speed (adjustable)
- minimum distance between vehicles (adjustable)

Determining the optimal start time for each station can be accomplished through a series of experiments. An initial sensitivity analysis has shown that significant impact on startup times depends on the energy consumption in the pools and ovens, as well as the relationship between fill levels of different areas. With start times ranging from 4am to 8am in 10-minute increments, the total number of potential experimental runs is up to 24^6. Since each run lasts 0.1 seconds, the entire set would take approximately 220 days to complete. However, since these runs represent only a fraction of the possible initial condition combinations, relying on this brute-force method seems infeasible. So, the experiments were based on a GA framework that includes the classical elements: chromosomes, population, crossover, mutation, fitness computation, and selection. By applying this simheuristic approach (see section 2.2), a near-optimal solution can be obtained in a very reduced simulation time and stochastic deviations are considered simultaneously.

The Siemens Tecnomatix Plant Simulation software provides a module for GA optimization, which allows the definition of genes and fitness calculations based on simulation results, while other processes such as mutation and crossover are already prepared. The starting points of the stations form the chromosomes. The algorithm generates the initial population and creates offspring through crossover and mutation. The offspring are then sent to a simulation for evaluation. After the simulation runs, it returns a fitness value to the GA based on its simulated results. The GA then selects among the offspring. After several iterations, a near-optimal solution is identified. In addition to reducing total energy consumption, two production-related constraints must be met: on-time delivery to the sealing line and preventing blockages in the E-Coat line. The problem of reducing total energy consumption can be described as delaying the heating process as long as possible. This assumes that the station's interior temperature is constant throughout the day and that the pool and oven temperatures are close to ambient before the morning shift begins. Once the pool or oven reaches its set temperature, a constant amount of energy is required to maintain the temperature.

$$\mathrm{fitness}_{\mathrm{En.}} = n \times \sum \mathrm{PowerDemand} \times \mathrm{OperatingTime} \quad (1)$$

Although the main target of this study is to reduce energy consumption in E-Coat line, meeting two production-related constraints is essential, namely on-time delivery to the sealing line and preventing blockage in the E-Coat line. The delivery's effectiveness is evaluated by computing the difference between the planned and simulated total output of the sealing process over a specific period. This is done by calculating the difference between the planned total output and the actual total output of the sealing process over a specific period, weighted by factor k. Additionally, the car body must not remain submerged in the pool for an extended period, as it can affect the quality of the E-Coat layer. Therefore, the smaller area between pool and oven, must not experience any blockages to avoid disrupting the continuous process. The blockage time is measured in reserve area before the sealing line.

To improve efficiency of the overall process, pre-experiments were conducted using extreme settings to determine the earliest and latest start times for the pools and ovens, thus narrowing the variable range. In the experimental procedure, the user provides inputs for the described initial setup parameters. Once these parameters are set, the GA-integrated experiment is run with a generation size of 20 and a population size of 40 to determine the optimal combination of start-up times for the equipment. The entire experimental process takes approximately one minute.

3.2. Applying simulation for validating batching optimization

In the second use case, coupling method 4 (see Section 2.2) is applied, since it still involves an iterative and partly manual release process, and the additional simulation is used to investigate stochastic effects and validate the planner's decision. When an order goes into production, the color and model of the vehicle are predetermined. The vehicle is identified by a unique chassis number that is linked to its color and body type, among other attributes. There are two categories of top coat paints used in the painting process: solvent-based and water-based. Depending on the type of paint assigned to the body, it is sent to the appropriate top coat line. The waterborne paints use the "Lotti Colori" platform to form a paint batch. This platform is a buffer area that precedes the top coat line. It is used to form different color batches in preparation for the subsequent color painting. There are three parallel buffer lines, each with the capacity to accommodate a defined number of car bodies.

A return lane and transfer lanes allow the bodies to move through the area in a predetermined direction. A dispatcher is responsible for building paint batches by sending car bodies to the appropriate buffer line and return lane. Upon completion of a paint batch, the car body is then sent to either a water-based or solvent-based line. If the color of the next car to be painted is different from the previous one, the nozzle must be cleaned and the paint changed, resulting in a certain amount of paint waste. Therefore, the primary goal of the planning process is to increase the batch size as much as possible while ensuring that there are always cars to paint on the waterborne line to maintain productivity. Thus, larger batch sizes result in fewer color changes, which reduces the environmental impact in two ways:

- Fewer color changes reduce the amount of paint sludge that must be disposed of or incinerated,
- Fewer color changes reduce energy consumption during unproductive (i.e. idle) times.

The loop area has a single buffer lane and a return lane, allowing cars to move continuously through the area in a cyclical manner, similar to a rotating conveyor belt or a revolving sushi restaurant. This area acts as a miniature distribution center, serving two important functions: cars not yet assigned to a buffer lane can remain in the looping area temporarily, and cars leaving the buffer area can be returned to the buffer via the return lane.

The buffer area consists of the remaining two buffer lanes, which serve as temporary storage areas on a First In First Out (FIFO) basis. As they exit the loop area, car bodies of the selected color are sorted based on the size of the batch they make up. These cars can either proceed to the top coat line for painting or be diverted to the buffer area to await the accumulation of additional batches of the same color to form a larger batch. The decision to send car bodies to the top coat line or to the buffer area depends on the minimum batch size, n, which defines the quantity required before cars can be released to the Top-Coat line. This parameter can be calibrated to the current load of the buffer area. The decision process is shown in Figure 3 below, with a minimum lot size value of 3. This value is set as a default based on the planner's experience but is fully customizable.

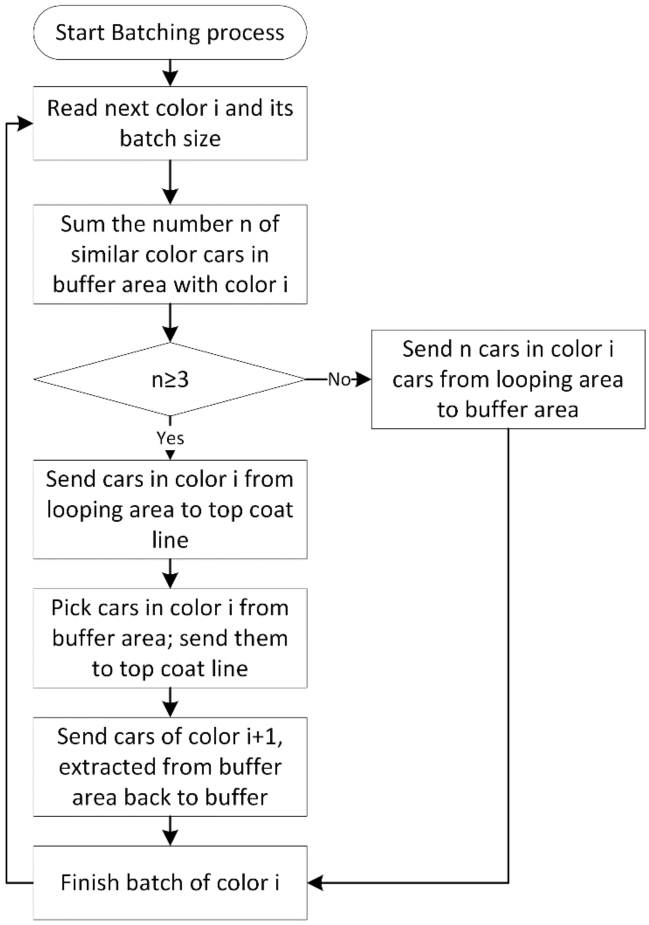

Figure 3: Decision-making process for vehicle batching

Since this is a new concept, it is essential to analyze its feasibility before putting it into practice. Several aspects need to be verified through testing and analysis:

1. Do the speed and capacity of the transport equipment meet the requirements of the system?
2. Can the production capacity of the top coat line be maintained with the proposed platform design?
3. Is capacity of the buffer area sufficient to store and process the incoming car bodies?
4. How much can the average batch size be increased and does it meet the production requirements?

To answer these questions, a discrete event simulation model was built using Siemens Tecnomatix Plant Simulation software to simulate the proposed batching strategy and validate the feasibility of the solution. The result of the simulation includes the total number of color changes in the top coat line and the average interval between cars entering the top coat line. After simulating multi-day production, the average paint lot size reached 5.72, whereas the average lot size before was between 3 and 4. The average delivery interval of the top coat line is about 67.7 seconds, and the computational optimization takes about 10 minutes of total processing time. In the occasional case of a high level in the buffer area, the problem can be solved by reducing the minimum allowed batch size. These simulation results demonstrate the effectiveness of the optimization solution and algorithm.

4. Summary and outlook

Material flow simulation, especially with discrete event modeling, has become a standard method for analyzing and predicting the behavior of production systems, with energy input and target criteria gaining importance for more than a decade. This has led to the combination of discrete production processes with continuous energy flow in simulations. The integration of additional environmental criteria allows for a more comprehensive assessment of environmental sustainability. In addition, there have been efforts to combine simulation with optimization, particularly in production scheduling.

The primary challenge in the E-Coat use case is to efficiently heat the tanks and ovens each morning, balancing energy consumption with the need for timely preheating. Traditionally, start-up times have been set manually without considering the reserve levels between lines, often resulting in premature heating and excessive energy consumption. The goal is to determine how reserve levels affect the optimal startup time and provide data-driven startup time recommendations. The goal of the batching process in the "Lotti colori" platform is to increase batch sizes to minimize color changes, thereby reducing environmental impact by reducing paint sludge and energy consumption during idle times. The system uses a heuristic approach and a simulation model for planning and validation. The generated results demonstrate the effectiveness of the proposed optimization solution.

There are a few assumptions that were considered during the model building and experimentation. For the E-Coat use case, this specifically refers to the fact that the heating curves for the pools and ovens are assumed to be uniform. More accurate physical modeling is possible, but the necessary data was not available and its impact on the overall startup sequence may be negligible from a logistical point of view. The batching process currently assumes that a scheduler provides an input list every 10-20 minutes, as online data was not available. This may be error-prone and will require future adjustment.

In the context of the ECOFACT project, the models are integrated into an online digital twin platform that serves as a single access point for a variety of decision support tools. The functionality and applicability of the tools will be tested in a structured validation phase. In terms of general scientific advances, the development of more sophisticated planning algorithms that take into account a wider range of variables could be a fruitful area of study. For example, machine learning techniques could be used to improve decision making in these complex systems.

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