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# Comparison of Simulation-based and Optimization-based Energy Flexible Production Planning

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**Abstract**

Due to an increasing use of renewable energy sources like wind and solar power, electricity generation becomes more volatile depending largely on weather conditions. This leads to fluctuating energy costs and gives new opportunities for cost savings to industry. Thus new ways of energy-oriented production planning will be necessary, without violating production related goals. The scope of this paper is the comparison of simulation-based and optimization-based production planning. Both approaches are compared in a case study with real data from an energy-intensive production. Evaluation criteria, for example computational effort, quality of planning and acceptance, are used to measure their operational capability.



*Keywords:* energy flexibility; production planning; optimization; simulation; renewable energy; sustainable manufacturing;

## 1. Introduction

With the United Nations Climate Change Conference in 2018 [1] and the agreement of the Conference in 2015 [2], following up the Kyoto Protocol [3], the promise to reduce the carbon dioxide emission became once more the center of public attention. In 2007, the EU's climate and energy package has been passed in order to reduce the negative environmental impact of human activities. This was the trigger for the German government to pass a concept for an ecofriendly, reliable and affordable supply of energy in 2010 [4]. In 2015, the share of renewable energy reached the mark of 30 % [5].

Because of the high industrial energy demand in Germany, which is 47 % of the annual energy demand [6], the flexibility of the industrial energy demand presents a relevant element to ensure a safe energy supply. These compensation measures offer companies the possibility to reduce their energy costs by taking advantage of fluctuating electricity prices. Therefore, an energy-oriented production planning is needed. This paper will present the implementation of a simulation and an optimization-based approach. Simulation and optimization time and quality are used to compare the two approaches.

Section 2 will introduce the energy-oriented production planning and will describe the needed functionalities. The comparison of both different approaches is based on the implementation for a certain use-case, which is described in Section 3. In section 4 the results of both approaches will be presented and discussed.


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## 2. State of the Art

### 2.1. Energy-oriented production planning

Production planning is the coordination of production orders in regular planning horizons. The areas of responsibility include lot size planning, capacity planning as well as scheduling. The task of scheduling coordinates the different orders and production lots on existing resources on the basis of pre-planned capacities. The result of the scheduling is transferred to the order release, which leads to the execution of the production process [7].

The performance goals of production planning are high delivery reliability and short delivery time of the production system. This is offset by the goals of the cost aspects, which include low production costs and low capital commitment costs. [8] In terms of costs, consideration of the resource energy has been the subject of research in production management for several years [9]. In addition to energy efficiency, as a ratio of required energy in relation to the benefits provided [10, 11], energy flexibility also gains in importance as part of the energy transition. The adaptation of energy consumption to energy availability [12] can be used by companies to save costs for the procurement of electrical energy or to generate revenue on reserve power markets [13]. This paper considers the proactive adjustment of consumption to price signals of the day-ahead market. This is due to the fact that the time horizon of the production planning permits the consideration of the day-ahead market, which trades electricity products up to one day before delivery. This is contrasted by the intraday market, which falls within the horizon of production control through trading up to 45 minutes before delivery [14].

With the increasing importance of the energy resource, and in particular due to the demands on flexibility, the tasks of production planning are becoming more complex. The use of simulation or mathematical optimization is usually unavoidable to solve the problems appropriately.

### 2.2. Scheduling Methods

Scheduling deals with the allocation of orders to resources in a certain period of time [15]. Resources such as the availability of machines or other manufacturing equipment have the property to be limited but not consumed [16].

A large number of scheduling methods have been established. According to Evers [17], those can be divided into optimizing, heuristics, priority rules and procedures from the field of artificial intelligence, as shown in figure 1.

Optimizing techniques for example include Linear Programming and Dynamic Programming [17]. These methods can identify the optimal solution under certain conditions, but usually take longer than heuristic methods.

Due to the complexity of scheduling problems, which belong to the group of NP-complete decision problems, and the large number of influencing variables that must be taken into account during scheduling, heuristics and priority rules have prevailed [17–20]. These procedures cannot guarantee an optimal solution. Moreover, the result cannot be used to estimate how far the solution found differs from the optimal solution [18].

The increasing use of methods from the field of artificial intelligence means that scheduling problems can also be solved with the help of these methods, e.g. neural networks [17, 18].

Another group that receives far less attention are simulation-based optimizations [20]. These differ from the previously mentioned methods mainly in the modeling. In simulation-based optimization, heuristics are often used to find a good solution, so that the same restrictions apply as for the methods mentioned above. Optimizing methods in combination with simulations are usually not suitable, since the assumptions that have to be fulfilled for optimizing cannot be verified, e.g. the linearity of a problem [20].

In order to solve a scheduling problem, it usually has to be converted into a model in the first step. Simulation in the field of production and logistics uses discrete event simulation for representation of the underlying problem [20]. When simulation software is used in production and logistic, the modeling in many software programs is graphically objectoriented with the aid of function blocks [20, 21]. For optimizations, a mathematical notation is usually chosen. Simple procedures such as priority rules can be based on simple models.

### 2.3. Energy-oriented Scheduling

Considering energy issues within production scheduling has been addressed by many researchers in the recent years. As a result of this, both optimization- and simulation-based approaches are applied. In the following, a preselection of relevant contribution is presented. A detailed review of optimization-based scheduling approaches to include energy aspects within production planning is given in Biel & Glock [22]. Keller et al. [14] presented an energy-oriented

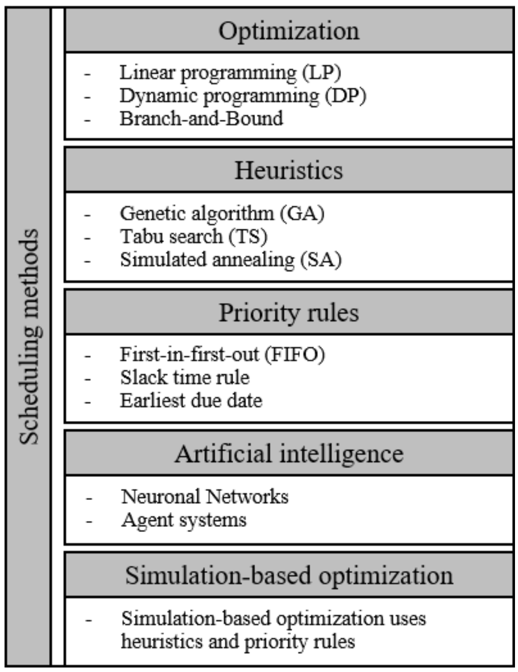


Figure 1: Scheduling methods in reference to [15].

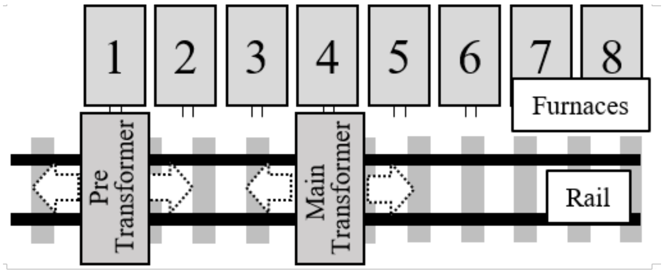


Figure 2: Graphitization furnaces and rail system.

scheduling approach of a production system in order to decrease energy costs. Variable electricity prices and self-supply are modeled. The heuristic approaches Simulated Annealing (SA), Genetic Algorithm (GA) and Ant Colony Optimization (ACO) are compared. A second example addressing total energy and labor costs of a production system is given in Gong et al. [23]. A memetic algorithm minimizes the multi-objective optimization function. The developed algorithm is applied in an extrusion blow molding process. Another multi-objective optimization problem is formulated in Dababneh et. al. [24]. The objective function consists of production maintenance and energy costs, thereby fluctuating energy-prices are considered. In this case a particle swarm optimization solves the mathematic model.

Furthermore, there exist various approaches which are based on simulation. A simulation-based optimization is implemented in Junge [25] to minimize the overall energy consumption of a production system. Out of several different optimization methods a genetic algorithm showed the best results. In Lorenz et. al. [26] periodic time-expanded networks are used for modeling. The aim was an optimized adjustment of starting time events of all processes to reduce peak-loads. The system thereby reduces the peak-load by about 20 % in a case study.

Eberspächer et. al. [27] presented a simulation-based approach to reduce the energy consumption of machine tools. A tool library was programmed in order to model the energy consumption in detail. The model is extended by an optimization model which minimizes the energy consumption by adapting the operation states. Further simulation-based approaches are discussed in Roemer & Strassburger [28].

The discussed scientific contributions make clear that both simulation-based approaches and mathematical optimizations are applied. However, the decision to use this method is poorly explained in those publications. In addition both approaches where never compared for the same problem in order to get a benchmark. This paper presents a comparison of a simulation to an optimization-based solution for the same energy-cost oriented production scheduling problem.

## 3. Use Case

Graphitization describes a heating process within the graphite production, in which a carbon material transforms into a graphite structure. The needed temperature of more than 2600°C is reached by electric resistance heating [29]. In the present case, eight identical furnaces are available for the graphitization. The electrical energy is transformed by two transformers and is being fed into the material to heat it due to its material resistance. In order to minimize conduction losses, the transformers are moved towards the furnaces via rails, as shown in Figure 1.

As a result, transformer 1 and transformer 2 are located on rails in a fixed order. Transformer 1 has only limited power, which is not sufficient to map the entire graphitization and is therefore referred to as the pre transformer. Transformer 2 is accordingly referred to as the main transformer. The heating is performed within two phases. Preheating ensures a constant temperature distribution in the material. After a holding time the second heating phase reaches the target temperature. The pre transformer can only provide enough power to realize the preheating, as shown in figure 3. By using the pre transformer for preheating, the process can be parallelized. As soon as the graphitization process has been completely passed through, the transformer can be dispatched. The graphitization material remains in the furnace to cool down before the furnace can be emptied. The transformer can be used at another furnace during the cooling process.

The aim is the energy-oriented planning of the graphitization process during the week, so that the energy costs are minimized. For this purpose, parallelization with the help of transformers and the temporal shift of the load cycle can be used. The planning is done for one week in advance on the basis of a weekly price forecast. Though all the given orders must be planned for the week, there is no given order or due dates earlier than the end of the week for any of them.

### 3.1. Optimization

The underlying use case was modeled in a mixed integer program (MIP). The objective function minimizes the overall energy costs needed by the two transformers to heat up the material. To minimize the objective value, the start time of an order and the use of a transformer were allocated. The granularity in time was 15 minutes. The objective function is depicted in function (1). To determine the total energy costs, the required power κ of each order $a \in A$ is summarized and multiplied with the price forecast $c$.

$$\text{Min} \sum_{t} \left[ \sum_{a} \kappa_{at} \cdot 0.25 \right] \cdot c_t \tag{1}$$

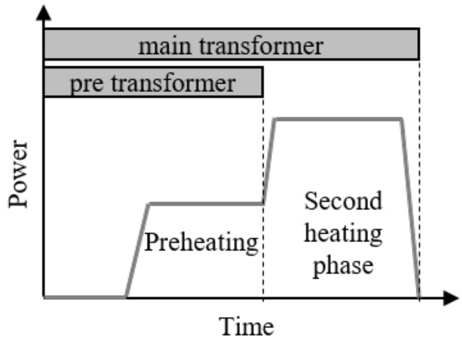


Figure 3: Graphitization process in reference to [10].

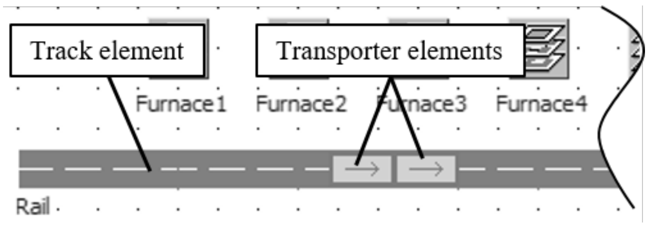


Figure 4: Realization of restriction (2) in Plant Simulation.

The constraints of the model implement the technical restrictions of the production system as described in section 3, e. g. the technical restriction describing the sequence of the transformers on the rail or the limited power of the pre transformer. Another part of the scheduling problem implemented by constraints are restrictions concerning the staff, such as predefined shift working times for different groups of employees. Those restrict the scheduling because a transformer can only be moved when staff is available. In total there are 44 constraints to depict the relevant processes of the graphitization. To solve the MIP a branch and bound strategy and a simplex algorithm were used.

As the focus lies on the comparison of the two approaches optimization and simulation-based optimization, the full model will not be supplied. As an example there will be a comparison between the restriction of the two transformers and how they are realized differently in optimization and simulation models. Explicitly the restriction that transformers cannot overtake each other will be analyzed. The associated function (2) is given below.

$$\sum_j \gamma_{0jt} \cdot j \leq \sum_j \gamma_{1jt} \cdot j \;\; \forall\, t \in T \qquad (2)$$

The binary variable $\gamma$ is 1 if the transformer i is placed in position j at time $t \in T$, otherwise it is 0. The position j corresponds to the furnaces, e. g. the main transformer ($i = 1$) is placed in front of furnaces 1 ($j = 1$), then the pre transformer ($i = 0$) has to be in position $j = 0$, which is left hand side of furnace 1. The equation is true if the position of the pre transformer has a smaller index than the position of the main transformer, which describes the desired outcome.

### 3.2. Simulation

In addition, the production system was modeled using the material flow simulation tool *Tecnomatix Plant Simulation*. For the modeling, the VDI 3633 [30] standardized modeling process was applied. In the first step, the objective of simulation is defined. Thereafter, the production system is analyzed in detail in order to determine to which extent every element of the production system has to be modeled. Thereby a bottom-up approach was applied. The information needed was gathered during expert talks and structured process recordings. The information about the production process was then translated into technical restrictions and were documented in a formalized form. In the next step the actual modeling in *Tecnomatix Plant Simulation* was realized. State transition diagrams are applied to indicate the process sequence. During all these steps, the data collection and data preparation were promoted.

As an example, in figure 4 the modeling of the two transformers is illustrated. Similar to the optimization, the restriction for transformers is realized in the simulation. Due to the use of *Tecnomatix Plant Simulation* a lot of functionalities can be realized by using integrated function elements. As shown in figure 4 the rail system is realized by the track and the transformers are displayed by transporters. The restriction that the transformers are not able to overtake themselves may be solved by applying those elements. Figure 4 shows that the second transformer is blocked as soon the first transformer stops. Furthermore the simulation as shown ensures that only one of the transformers is connected to a furnace and also that a transformer cannot be connected to more than one furnace at the same time. Those restrictions have to be explicitly modeled in the MIP separately.

After the relevant part of the underlying production system was completely modeled, the simulation-based optimization was implemented. Therefore the resulted system model was extended by a Genetic Algorithm. Because of the limited functions of the given Toolbox in *Tecnomatix Plant Simulation,* the scheduling problem had to be transformed into a single sequencing problem. Therefore, a decent number of dummy orders of 15 minutes and a consumption of 0 kW each were generated. Thus considering the single carbonization order and dummy order for each furnace, the total utilization resulted in 100 %. The resulting sequencing problem aims to optimize the sequence of production and dummy orders and thus is able to flexibly schedule the production orders within in fixed intervals of 15 minutes. In case dummy orders are scheduled, there is no production running. The experiments were made using the fixed number of 50 generations and a population size of 120. The fitness was measured by the total energy costs over the planned week.

### 3.3. Results

After modeling and validating the models, a use case was implemented, where several weeks, of the actual production program of the industrial partner, were planned. For both methods, the same orders and energy price forecasts were used.

The results differ in the sequence in which the orders are planned. Nevertheless the total energy costs do not differ in 80 % of the cases. A significant difference can be observed in 20 % of the cases, by a lower energy cost consumption of 1.4 % by the MIP optimized production plan.

In terms of computing times the simulation-based optimization solved the scheduling problem in about 30 min. The mean computing time for the MIP is 19 hours. The summary of the results is given in Table 1.

Table 1. Summary of the results.

| | Simulation | Optimization |
|---|---|---|
| Computing time | 30 min | 19 hours |
| Quality of solution | Near to Optimal 20 %<br>Optimal 80 % | Optimal |
| Modeling effort | High | Very high |
| Acceptance | High | Low |

The modeling effort was based on the descriptions in section 3.1 and 3.2 where the differences in implementation of constraints were discussed. The acceptance was observed during discussions with participating project partners.

## 4. Discussion and Outlook

The results show that simulation-based optimization can achieve similar optimization results as mixed-integer programming. The genetic algorithm integrated in *Tecnomatix Plant Simulation* often finds a result close to the optimal solution. Only in 20 % this was not the case.

The calculated results were also compared to the manual planning in the company. The manual planning is done by a planner, who tries to shift the cycle by hand to fit them into times with low energy prices. The improvement to manual planning is in the range of 5 % per week. Percentages in the single-digit range do not seem to be particularly good. Against the background of energy-intensive processes, where energy is the main cost factor, this has a high leverage.

The results are offset by a shorter average computing time on the simulation side and a graphical representation of the problem. The computing time for solving the MIP has fluctuated depending on the input data. In principle, a computing time in the range of several hours is not practicable. Since the results of the simulation-based optimization were often hitting the optimum, a resetting of the genetic algorithm could be a next step to reduce computing time even though the computing time was lower for the simulation-based optimization. This can be realized by adjusting the setting of the Genetic Algorithm, e. g. reducing the number of generations. Also a heuristic approach to solve the MIP can be a valid task, since the solution quality of heuristics seems to be high. Therefore an improvement of the computing time is to be aimed at, without losing the result quality substantially.

In addition to the lower computing times, the graphic representation of the simulation model makes it easier to understand the model. Especially to promote the acceptance of people outside the field of Operation Research, e. g. the production planer and the process engineer, this is a huge advantage, also when validation is performed. However the mathematical representation of the problem can only be explained with difficulty to a nonspecialist. Another strength of simulation has not yet been considered in our case. A simulation is predestined to consider stochastic events. This could be the next step to further develop the model. A large number of stochastic events can be simulated in advance or a reassessment can be carried out within the framework of a real-time simulation if an unexpected event occurs in reality. The central requirement for a real-time simulation use is a short computing time, which has not yet been fulfilled by the presented solution approaches. One possibility to reduce this time can be a modularization of the simulations into smaller partial problems. The long computing time was also due to the fact that additional complexity was introduced into the simulation with dummy orders. In addition to the computing time, the complex modeling was identified as a further challenge in the results. In order to reduce the effort and to implement an energy-oriented production control in further companies, an automated modeling and parameterization has to be developed. This contributes to an improvement of the underlying input data and consequently to an increase of the simulation quality.

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