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Simulating the Energy Consumption of Machines in Compound Feed Manufacturing for Investment Decisions

Simulation des Energieverbrauchs von Maschinen in der Mischfutterproduktion zur Unterstützung bei Investitionsentscheidungen

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Abstract: The manufacturing of compound feed is subject to highly dynamic influences. On the one hand, compound feed is usually manufactured in a make-to-order production mode, whereby a great variety of ingredients can be used to manufacture the same end product. In the use case presented, the energy consumption of the manufacturing process constitutes a major factor for an efficient production. This contribution presents an approach to learn process- and corresponding simulation models from historic production data, which enable an estimation of the respective energy consumption. Therefore, the modelling method 'Micro – Process Planning and Analysis' is extended and applied to this use case. As a result, the article presents a simulation study to assess the energy efficiency of different types of presses. The conducted simulation study shows highly different efficiencies with respect to different types of presses based on a dataset covering several years of production.

1 Introduction

During the last decades, a continuous trend towards customer driven markets can be observed. As a result, an increasing number of companies focus on make-to-order production modes, whereby products are manufactured based on customer demands (Kuo et al. 2016). Such production modes are faced with high dynamics when it comes to production planning and scheduling. Moreover, investment decisions, e.g. for new machines or workstations, cannot be made simply based on the actual product portfolio but need to incorporate information about the structure, types and frequencies of customer orders. This article investigates the use-case of an agriculture company producing compound feed in a make-to-order manner for an agricultural cooperative society. Thereby, customers usually place orders on the same day the product is manufactured. As market prices for raw materials vary, the composition of products can change for each order on a daily basis, resulting in strong dynamic influences on the products configurations. In terms of the presented use case, a reduction of energy costs presents a major objective for an efficient production. At this, the energy costs vary for different raw materials and product compositions, as some can be processed more efficiently than others. Moreover, energy costs strongly depend on the chosen types of machines, which in this case refer to grinders or presses.

This article focusses on methods to learn suitable process models to combine discrete-event simulation of logistic processes with cause-effect networks. This enables an estimation of the energy costs based on available raw materials and machines. In terms of production planning, the resulting simulation models can be used to select the most efficient machines for each order. Moreover, the article presents an approach to support investment decisions by simulating the expected energy costs for machines using larger sets of historic production data to capture the customer behaviour.

1.1 Process Chain Planning, Configuration and Simulation

Within the literature, there are only very few approaches which allow a combined planning and configuration of process chains. During the last years, different articles focused on the configuration of specific processes (cf. Afazov 2013). Thereby, the configuration relies on detailed studies of the corresponding processes and is usually supported by very detailed physical models in form of finite element simulations (e.g. Afazov et al. 2012; Pietrzyk et al. 2008). Another approach found in the literature focusses on the use of sample data (historical or experimental) as templates for the configuration (e.g. Sabotin et al. 2009). Although both approaches enable a precise configuration of single processes, they cannot be transferred to other processes or products easily. In the context of process chain planning, classic methods like event-driven process chains or the Unified Modelling Language (UML) are used commonly. Whereas these methods do not include the configuration of processes, Denkena et al. (2006) proposed an approach that indirectly addresses this topic. This approach builds upon the modelling concept for process chains (Denkena and Tönshoff 2011), whereby operations are interconnected by so called technological interfaces. In general, these describe sets of pre- or post-conditions for each operation. Although this approach enables configuration of the processes, the creation of these models requires a very detailed insight into the processes.

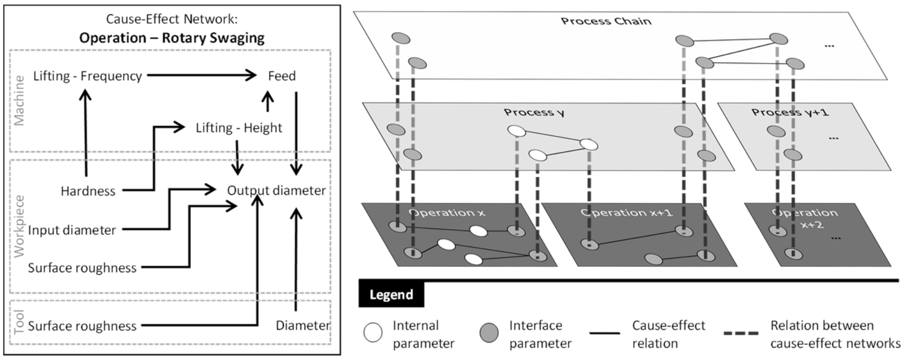
1.2 Simulation Model Generation

Most of the methods described before rely on specifically designed process models for the configuration and design of process chains. Nevertheless, the potential of a (semi-) automated generation or learning of simulation models is comparably high. According to studies, about 80 percent of the efforts involved in a simulation study can be automated (Baier and Krieg 2008). In general, this topic has been part of scientific research in the context of the digital factory concept during the last decade (Wenzel 2009). Basically, two different approaches to generate simulation models exist. Data-driven methods rely on data mining techniques to instantiate or configure simulation models (Huang et al. 2011), while other methods such as graphical modelling methods use specific notations to create the underlying simulation models. In this context, a number of different graphical modelling or transformation approaches exist, which either extend current modelling languages (e.g. Batarseh and McGinnis 2012) or provide adapted meta-models (e.g. Cetinkaya et al. 2010). Usually, these methods focus on the material flow and thus do not allow to assess specific characteristics or parameters like energy consumption based on changing inputs, like varying raw materials.

2 Modelling Framework and Methodology

In order to build the simulation models, this article investigates the method transfer of the "Micro Process Planning and Analysis" (μ-ProPlAn) Methodology (Rippel et al. 2014a) for the estimation of energy costs in the production of compound feed. The methodology itself allows using both expert knowledge as well as data mining techniques to create process models and to generate simulation models based on these. While the methodology is originally being developed for micro manufacturing (c.f. Rippel et al. 2014b; Rippel et al. 2016), it provides a set of tools to model, characterize and evaluate process chains that are subject to high variations and difficult to describe influential factors (Rippel et al. 2017) using statistical as well as predictive models. Therefore, the methodology uses so-called cause-effect networks to characterize interrelations between production relevant factors. Using these cause-effect networks, process chains can be developed and evaluated regarding their economic and technical feasibility using discrete-event material flow simulations directly generated from these process models.

The modelling notation consists of three different views, corresponding to different levels of detail. The first view focusses on the top-level process chains. This view's notation closely follows the classic notation of process chains (please reference (Denkena and Tönshoff 2011) for more details). As an extension to the classical approach, all process elements are connected using process interfaces. These interfaces also include logistic parameters in addition to the original technical parameters. The material flow view further describes operations by assigning material flow objects that are used to conduct the operation (e.g. machines/devices, work pieces, tools, operating supplies or workers). This enables the modelling of specific production scenarios with specified resources and allows an evaluation of the models regarding logistic aspects. At this, μ-ProPlAn offers the option to conduct discrete-event material flow simulations based on the specified production system and the modelled process chains. The third view focusses on the configuration of the processes and process chains using cause-effect networks to describe the inter relationships between relevant process parameters. Each network consists of a set of parameters and a set of cause-effect relationships, forming a directed graph. The set of parameters consists of all technical and logistic characteristics that are relevant to describe the object's influence on the production process. In case of work pieces these can be material properties or costs per unit. As for processes, these include production rates, forces or other characteristics that can be set, calculated or measured (Fig. 1a). From a modelling perspective, cause-effect networks are hierarchical. Each material flow object (work pieces, machines, tools, etc.) holds its own cause-effect network, or at least a set of describing parameters. When combining these single elements to operations, process elements or process chains, higher level cause-effect networks are created by describing additional relationships between the parameters of the networks or by connecting them to previously specified process interfaces (Fig. 1b).



(a) (b)

Figure 1: *(a) Composition of an operation (according to Rippel et al. 2014b) (b) Composition of higher level cause-effect-networks (Rippel et al. 2014a).*

The creation of cause-effect networks is divided into two steps: the qualitative modelling and the quantification. The quantitative model of the network is created by collecting all relevant parameters and denoting their influences among each other (Fig. 3a). The quantification as second step, focusses on enabling the propagation of different parametrisations throughout the network. In case of well-known relations, µ-ProPlAn allows to enter mathematical formulas directly. In addition, it offers the capabilities to quantify cause-effect relations from experimental- or production-data by applying methods form the areas of data mining (e.g. artificial neural networks, support vector machines, regression trees or local regression methods) and statistics (e.g. linear or polynomial least-square regressions). For a more detailed description of these methods, please refer to Rippel et al. (2014a) and Rippel et al. (2014b).

3 Use Case Description and Simulation Study

To enable the generation of simulation models, suitable process models have to be created. In a first step, the overall process chain is being developed. In this use case, the process chain consists of two relevant processes: Grinding and Pressing. In a second step, the involved resources are incorporated into the model. The third step consists of the creation and quantification of the corresponding cause-effect networks to obtain suitable process models for the simulation.

3.1 Use Case: Manufacturing of Compound Feed

Compound feed manufactures focus on the refining of raw materials like grains to animal feed like flour, pellets or crumb feed. The described compound feed manufacturer is a service provider mainly producing feed for an agricultural cooperative society. This society provides the recipes for the products, buys the raw materials and retails the end products. The compound feed manufacturer produces the products for fixed prices and the only opportunity to maximise the profit is to safe energy and therefore energy costs. Due to the variety of costumers, the compound feed manufacturer produces 119 different feed recipes with over 60 different ingredients by daily variation of components and short-term orders by customers. At this, the energy consumption fluctuates strongly, as different feed recipes are manufactured with different machine parameters.

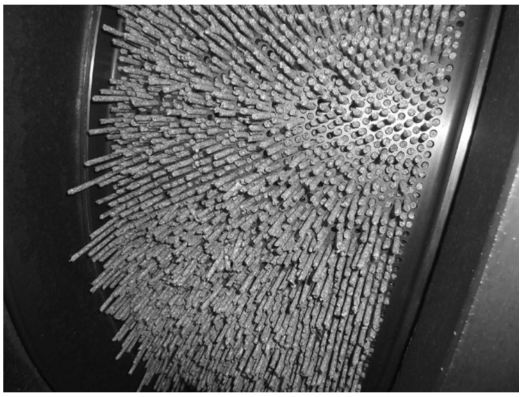


Figure 2: *Pellets leaving the press (DVT 2017).*

When compound feed processing starts, the ingredients are automatically dosed and weighed based on the feed recipe. The manufacturing begins with the grinding of the raw materials. There are two different possibilities to grind the raw materials: either by the use of hammer mills or in a combination of hammer mills and roller mill. The major difference is the feed-flour. If the feed-flour is produced by the use of hammer mills, the particles are fine-grained, whereas a feed-flour produced using the roller mill has a rougher particle size. The different grain sizes thereby influence the energy consumption and the steam conditioning during the pressing process. In a second process step, the flour is pressed into the required shapes (usually pellets as shown in Fig. 2). Therefore, the company described uses three different presses each with interchangeable matrices. These matrices define the diameter and the length of the pellets. Consequently, the presses configuration (matrix, tantrum distance) must be adjusted to fit the corresponding feed recipe, resulting in different throughput rates. Each machine is equipped with energy measurement systems, to monitor its energy consumption. In addition, three diode array based spectrometers (NIR) are installed to acquire characteristics of the ingredients and products like the humidity, protein or fat contents. These parameters are measured after the delivery of the raw materials, the grinding process and the pressing process. Another measurement system is the computerized particle analyser (CPA) which is integrated after the grinding process to analyse the grain size before the pressing process. The aim of these sensors is to provide a sufficient amount of information for the development of a control system, which optimizes the energy consumption throughout the process chain while retaining a sufficient product quality.

3.2 Cause-Effect-Network (Process Model)

Using the description of the process and a dataset of 2297 production runs, several relevant objects and parameters are integrated into the model. The overall objective of this model is the estimation of the energy consumption, focussing on the pressing process. Fig. 3 shows the resulting (simplified) qualitative cause-effect network. For this cause-effect network, the energy consumption is divided into the energy consumption of the pressing and the additional energy consumed by adding steam during pressing. The latter depends on the targeted temperature of the steam (usually 90°C) that is added, as well as the temperature and humidity of the used flour. The energy consumption of the pressing depends on the throughput and the overall duration. Thereby, these values depend on the total amount of flour used as well as on its characteristics in terms of grain uniformity and average grain sizes. On the material side, the dataset lists 119 different ingredients. A single product is related to an average of 23 of these ingredients, which can be used in different combinations and amounts. During grinding, these ingredients are processed into flour, whereby the flour's grain sizes (normally distributed) and humidity basically depend on the type and amount of raw ingredients used in its preparation.

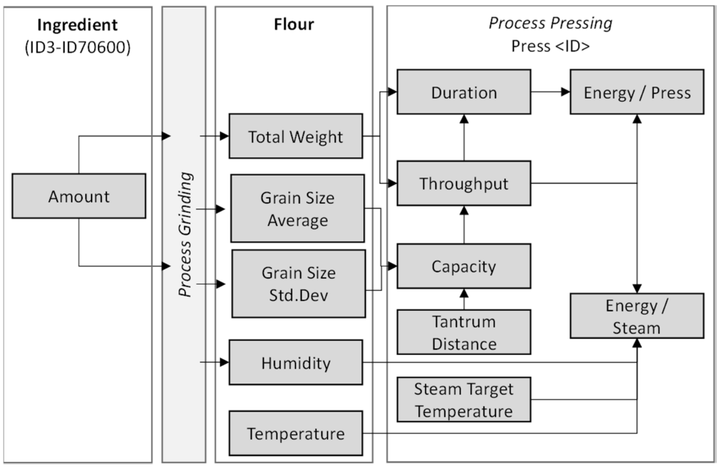


Figure 3: *Simplified Cause-Effect-Network for the Pressing Process*

The datasets used in this study incorporate production data of three different presses. Therefore, the µ-ProPlAn model incorporates three production devices, corresponding to one type of press. Each of these presses is assigned the previously described cause-effect network and is quantified using the corresponding entries of the dataset. In addition to the production devices, two types of workpieces are modelled: the flour and the ingredients. While the flour element is simply assigned the corresponding parameters as shown in Figure 3, all ingredients are subsumed in a single workpiece model element, which is then assigned one parameter for each of the relevant ingredients. These parameters describe the amount of that specific ingredient used. While this diverts from the usual way µ-ProPlAn models are designed, it strongly reduces the amount of material flow elements and thus the effort in creating the corresponding process model. Moreover, in terms of the simulation study described in the next section, this drastically eases the creation of different scenarios, as adding and removing material flow elements has yet to be performed manually within µ-ProPlAn, while the method can easily be extended to load and calculate different parametrisations directly. To further simplify the model, the grinding process is not incorporated into the models. Thus, the flour's grain statistics (mean and standard deviation) as well as the humidity are estimated directly, based on the used ingredients. The flour's total weight is calculated by adding up the single amounts and the process duration is calculated by dividing the total amount by the throughput rate. To quantify the remaining parameters, regression models are learned. Table 1 summarizes these models. The column "model" describes the model used for the parameter. In this use case, all parameters are either defined using a formula or using a locally weighted linear regression model (LWL) for their prediction. The LWL models are learnt using an Epanechnikov smoothing kernel spanning an average of at least 64 neighbouring sample points within the dataset. The column "Cor." depicts the regression's Pearson product-moment correlation coefficient. The column "Err." provides the models root mean squared error. Both values are derived using a ten-fold cross validation over the training sets. In order to approximate the flour's characteristics based on different combinations of ingredients, the complete dataset is used as training set. In contrast the three different models for the press types, only a single model was learned and is provided in the first two columns of Table 1.

Table 1: *Configuration of the cause-effect network*

			Press 1		Press 2		Press 3	
	Parameter	Model	Cor.	Err.	Cor.	Err.	Cor.	Err.
Flour	Weight	Sum of ingredients	-	-	-	-	-	-
	Grain Size (avg)	LWL	0.79	0.27	-	-	-	-
	Grain Size (Std.Dev)	LWL	0.63	0.11	-	-	-	-
	Humidity	LWL	0.84	0.92	-	-	-	-
Pressing	Duration	Amount / Throughput	-	-	-	-	-	-
	Throughput	LWL	0.98	2.36	0.87	4.16	0.91	4.96
	Energy Steam	LWL	0.68	7.74	0.82	9.67	0.84	8.49
	Energy Pressing	LWL	0.88	11.90	0.59	2.51	0.72	1.19

4 Simulation and Framework Extension

While the model described in the last section can be used for the selection of a specific resource during production, it provides the opportunity to assess the overall efficiency of specific type of press. As the company considered in this use case is heavily involved in a make to order production mode, the efficiency cannot be assessed without regarding the types and structures of customer orders. In order to compare the energy efficiency of different types of presses, this section describes a simulation study conducted using the process model derived in section 3.

4.1 Framework extension

To perform these simulations, µ-ProPlAn's change propagation module is extended. In general, the change propagation conducts a time continuous simulation to calculate the values for each parameter. Usually µ-ProPlAn instantiates workpieces according to the provided orders and simulates the material flow using parametrisations derived from the cause-effect networks. By diverting from µ-ProPlA's proposed modelling conventions and subsuming all workpieces (ingredients) into a single element (compare section 3), each order can be interpreted as a distinct parametrisation of the same workpiece, thus neglecting the material flow aspect of the simulation. Moreover, as each order corresponds to a fixed, non-changing set of parameters across the process model, the change propagation will eventually reach a stable state for all parameters. To enable simulations for such use cases, in which the overall structure remains static but the parametrization changes consistently, the change propagation is extended to directly apply input parameters from the dataset, run the simulation, record each stable state as well as its targeted value (if available) and proceed to the next configuration. In general, this extension allows a simplified simulation of different parametrisations if the overall process (chain) remains static.

4.2 Simulation Scenarios and Results

To evaluate the energy efficiency, the customer behaviour is replicated using historical data, spanning approximately 640 days. First, the overall accuracy of the process model is evaluated. While the characteristic values provided in Table 1 show that each parameter is characterized quite well, the overall precision of the cause-effect network can differ due to an accumulation of errors. Thus, in a first study three simulation scenarios are used to compare the estimated consumption to the actual one recorded in the dataset. Therefore, each simulation focusses on a single type of press and simulates all orders, which were actually run by the specific press. In a second study, the overall energy efficiency of the different presses is assessed. Therefore, only a single type of press is used to manufacture all orders recorded in the dataset.

Table 2: *Simulation Results*

Scenario	Acc. Steam	Acc. Pressing	Energy Steam	Energy Pressing
Type 1	-0.14 %	0.77 %	100.00 %	100.00 %
Type 2	-0.36 %	0.03 %	98.03 %	78.05 %
Type 3	0.51 %	-1.28 %	98.07 %	62.65 %

Table 2 summarizes the simulation results for both studies. Thereby, the columns "Accuracy" (Acc. Steam and Acc. Pressing) depict the relative error comparing the sum of all predictions to the sum of all actual values for the energy consumption within the dataset. These values show that the cause-effect network's overall estimation error is relatively small (at max at 1.28 %). The columns "Energy" present the relative energy consumption for the second simulation study. Thereby, all orders were simulated using only a press of the stated type. For the table, the most expensive press (Type 1) was selected as 100 % of energy consumption. Thus, lower percentages show that according to the simulation, other presses would only consume a portion of the energy. As a result, presses of type 3 would only consume about 63 % of the energy consumed by presses of type 1, calculated over all the orders within the dataset.

5 Discussion and Future Work

The article investigates the application of the modelling methodology µ-ProPlAn for the estimation of the energy consumption in the production of compound feed. Therefore, a process model is derived using a dataset of historical production runs. The resulting process model is used to simulate the energy consumption of three different types of presses. While the results in Table 2 show that presses of type 3 require only a fraction of the energy consumed by the other types of presses, the simulation study provided in this article only focusses on the energy consumption with respect to processing. In order to capture the financial impact of each type of press completely, additional factors have to be considered. Therefore, future work will aim to extend the model and the simulation, e.g. by considering processing times and capacities within the simulation or by evaluating investment and maintenance costs for the different types of presses. To enable an efficient simulation of scenarios, in which the overall process chain remains static but the composition of certain elements (i.e. raw materials) changes per order, the change propagation component was extended by means for efficiently managing and evaluating different configurations of the same static process chain. As depicted by this article, these changes enable an application of µ-ProPlAn to scenarios, in which more or less continuous streams of commodities are investigated. At this, the change propagation component is used to simulate these continuous streams, in contrast to the discrete-event simulation which is used in scenarios where different products or highly different components (e.g. in assemblies) are investigated.

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