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Challenges of manufacturing for energy efficiency: towards a systematic approach through applications of machine learning

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Abstract

Paper aims: Due to increasing energy prices, manufacturers have to pay more attention to the energy efficiency of their production processes. This paper aims to support manufacturers in increasing processes' energy efficiency by using production data and applying machine learning approaches.

Originality: Systematic guidelines or standards for minimising the energy consumption of manufacturing processes through machine learning approaches are still lacking. This gap is addressed in this paper.

Research method: The paper follows a qualitative research method to understand the manufacturing processes and their challenges in improving energy efficiency. The raw data for a 5-step approach were collected in research projects with manufacturing SMEs, and information about the processes through interviews and workshops with them. Then, an analysis of currently available machine learning frameworks and their selection and implementation is conducted.

Main findings: The main result is a 5-step approach for increasing the energy efficiency of manufacturing processes through machine learning. Essential applications and technical challenges for data mapping, integrating, modelling, implementing, and deploying machine learning algorithms in manufacturing processes for increasing energy efficiency are presented.

Implications for theory and practice: The findings can guide manufacturers, researchers, and data scientists to use machine learning in practice when they intend to increase the energy efficiency of manufacturing processes.

Keywords

Energy efficiency. Manufacturing processes. Machine learning.

1. Introduction

The manufacturing sector is one of the biggest energy consumers in the world. Some studies show that more than one-third of the overall consumed energy is attributed to industrial use (International Energy Agency, 2017). On the one hand, current energy policies impact energy costs. The excessive costs drive manufacturers to seek solutions for more sustainable production with less environmental impacts, such as reducing energy consumption. On the other hand, customers demand multiple functionalities for their products with higher quality than in the past. Therefore, today's manufacturers need to think of new criteria and approaches for improving the quality of their products while saving energy at the same time.

In manufacturing, the objective of a process is the creation of value with a predefined quality (Deutsches Institut für Normung, 2015). A manufacturing process under particular settings consumes a certain amount

of energy. In practice, the potential for energy savings depends on the type of products to be manufactured, their requested quality and the process settings. In this study, interviews with manufacturing companies were the basis of the first understanding of product specifications and operating conditions. Further, as the energy consumption of manufacturing processes is in focus, several challenges have to be overcome. The following difficulties are observed in the industry sectors of feed manufacturing, food processing and waste management:

Challenge 1: Lack of transparency about energy use. There is no precise mechanism to access real energy consumption or no clear understanding of the term energy efficiency (EE); for example, which manufacturing process demands the most energy and what parameters (variables) affect the energy consumption of the respective process. Therefore, there is a need for more visibility of energy information.

Challenge 2: Need for structured product and process-related data. When it comes to product and process data, knowledge about the product's behaviour in combination with the process is based on the employees' experience. Moreover, data are not available in a structured way. Data can be a crucial enabler in achieving energy efficiency. Process-specific data can be recorded through sensors in manufacturing processes. Yet, collecting the correct production data regarding energy consumption is often missing. Moreover, even if the structured data are available, there is a need to ensure data quality, right feature selection, transferability and sharing.

Challenge 3: Reliability on measurable values. A lack of employees' sensibility to energy saving potentials, fear of negatively influencing the manufacturing processes, and no time to care for energy efficiency due to day-to-day business are issues that manufacturers face when they initiate energy-saving strategies. Moreover, sensors as electrical devices can fail or be damaged in specific cases.

Challenge 4: Adapt to future digitalisation and automating manufacturing processes. Workflow in future manufacturing plants tends to be upgraded to digital or automatic. Therefore, the manufacturers should get ready for this change. When digital technologies are planned, there is often no practical guideline or standard available for selecting proper technologies and application of respective methods.

This paper proposes a 5-step approach for addressing the mentioned challenges. The focus of improving energy efficiency is through using data from manufacturing processes and applying machine learning methods. Machine learning (ML) methods can be used for learning complex relationships from massive production data and converting them into a basis for decisions and actions (Hecker et al., 2017). Decisions and activities in the current paper address understanding energy consumption in existing processes under particular settings for adjusting process parameters. The reason for choosing ML is that it is possible to find complex patterns in data by understanding the relationships between process conditions, energy, and product quality through these methods.

The 5-steps approach contributes to developing machine learning systematically, from collecting, pre-processing, modelling with ML, deployment and thus, using production-related data. These steps contribute to answering the question of energy savings for the same product quality at existing processes. Within each step, this paper identifies the technical challenges of ML and presents a path for their implementation.

This paper is structured as follows: Section 2 provides the state of the art of research in energy-efficient manufacturing (EEM) and frameworks for implementing ML in industry. Section 3 shows the research methodology of this paper. Section 4 provides the 5-step approach for increasing energy efficiency through ML. Section 5 shows a case study of the implementation of 5-steps. Finally, section 6 provides an evaluation of the approach and discusses its generalisation. Section 7 draws the conclusions.

2. State of the art

This section defines the terms energy efficiency and manufacturing processes firstly, to show the boundaries and viewpoint of this paper. The definitions are selected from the literature. Next, subsections 2.1 and 2.2 review the relevant state of the art of the research.

Energy efficiency: Is defined as "[...] reducing the consumption of energy, which refers to energy efficiency from an engineering point of view" (Irrek & Thomas, 2008, p. 1). The German Engineers society defines energy efficiency as "[...] the relationship between the result and the energy used" (Verein Deutscher Ingenieure, 2019, p. 2). The goal of this paper in terms of energy efficiency can be concretely stated as "to decrease the specific energy consumption of a processing unit while preserving the quality of end product". Therefore, only the direct energy used by a processing unit is considered in this paper. Often, valid data on indirect energy consumption is insufficiently available. On the one hand, it is essential to preserve the quality of the end product at a level in which the customer is satisfied and product specifications are not negatively affected. On the other hand,

reducing specific energy consumption can adversely affect product quality. Therefore, an optimised state can be achieved through modelling and better control of manufacturing processes.

Manufacturing processes: The purpose of a process is the creation of material goods (Deutsches Institut für Normung, 2015). In manufacturing, these goods are referred to as products. A product represents an output in the marketplace, which satisfies the customer's needs. Notably, in this paper, the transformation of a particular product A into a specific product B during a process will be analysed from the energy perspective.

2.1. Increasing energy efficiency in manufacturing

For energy management and successful implementation of energy efficiency programs, standards such as ISO 50001 for energy management (International Organization for Standardization, 2018) and DIN EN 16247 (Tuev, 2020; Bundesamt für Wirtschaft und Ausfuhrkontrolle, 2020), for the planning and implementation of energy audits, already exist. Several manufacturers prefer DIN EN 16247 because it provides a simplified version of energy management systems and focuses more on the practical implementation of measures for energy efficiency. Although ISO and DIN standards for energy and environmental management exist, there is still less focus on standards of data-driven approaches for conserving energy.

In contrast to general standards, increasing energy efficiency through quantitative or data-driven analysis is recently gaining more attention. Among journal publications, Narciso & Martins (2020) presents a review of machine learning tools for energy efficiency in the industry. Ahmad et al. (2022) address artificial intelligence (AI) as a driver for recent technologies, which are influencing energy systems. They conduct a review of AI applications in the energy value chain. Blesl & Kessler (2018), Herwig (2016) and Thiede (2012) give insights into energy analysis and management through methods, such as process modelling, simulation and thermodynamics. Potentials for manufacturing energy conservation through data-driven approaches are reported in Song et al. (2018) and Nabati et al. (2020).

Some other authors have also provided frameworks. For instance, a framework for systematically measuring resource consumption and later guiding decisions for optimising material and energy flows are proposed in Zhong et al. (2016) and Seow & Rahimifard (2011). DuttaGupta (2017) provides a conceptual framework for using machine learning for energy efficiency in small and medium-sized (SME) manufacturers. Mills et al. (2008) formulate best practices for defining strategies for energy-efficient manufacturing. However, they all do not prioritise the energy analysis in higher consumers (machines) or energy-intensive manufacturing environments. If energy costs exceed of total turnover, the manufacturing companies are considered energy-intensive (Gleich et al., 2012).

Recently Tan et al. (2021) published a framework called "machine learning for smart energy". Their paper addresses principal issues such as numerous machines, energy disaggregation per machine, state and complexity of processes.

In general, suggestions of appropriate techniques of ML, frameworks from practical experiences, means of deployment and effectiveness of the results of data-driven analyses for energy efficiency are not adequately addressed.

2.2. Data science frameworks for manufacturing

In this section, an overview of available data science frameworks is exhibited. These frameworks are selected based on the following criteria: (1) they can be used for applications of ML in EEM, (2) they provide a focus on processes or (3) they use the latest technologies in ML or related fields.

Cross-Industry Standard Process for Data Mining (CRISP-DM) (IBM, 2011) is a standard for applying techniques of ML to the industrial context. The methodology of CRISP-DM divides the process of data mining into five phases: business understanding, data preparation, data modelling, evaluation and deployment. Among data science frameworks, CRISP-DM is the mainly applied ML framework in manufacturing; for example, see Thiede et al. (2020). Although this standard is valid, it describes the data science life cycle with no specific focus on energy efficiency for processes. SEMMA and KDD (Pyvovar, 2019) are other data mining frameworks (see Figure 1). However, CRISP-DM is more comprehensive than them. Other standards, such as DevOps (DevOps, 2020) and Scrum (Scrum Alliance, 2015) can address the development of ML as software in an agile working environment as well as provide IT infrastructure for ML. ISO quality management standard (Deutsches Institut für Normung, 2015) guides through the management and organisational aspects of IT in manufacturing projects. MetaFlow, established by Netflix, addresses the deployment of machine learning for long-term use (Metaflow, 2021). Machelangelo (Uber, 2017) includes the application of ML/AI for solving special applications in transportation.
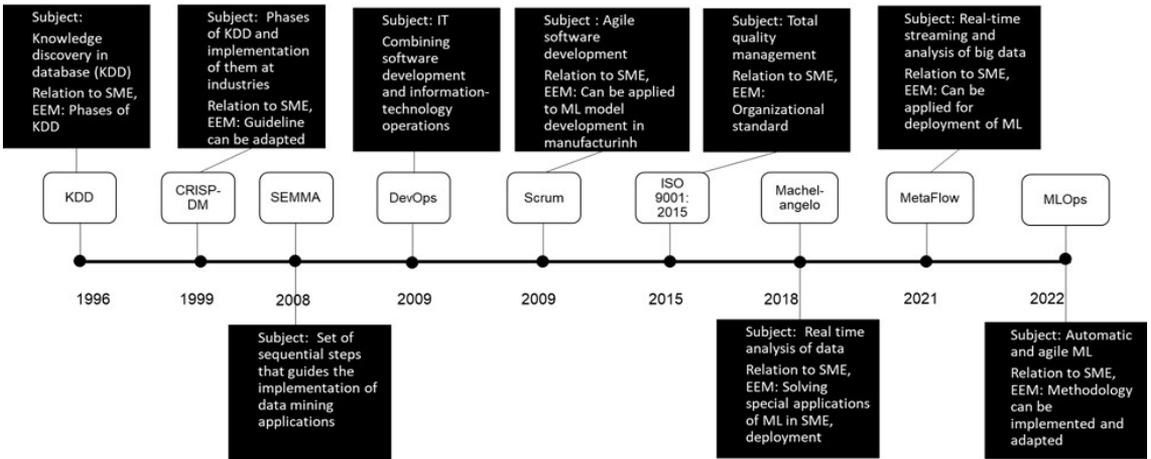
Figure 1. Current ML frameworks and their relation to EEM.

Very recently, as of 2022, a new framework AutoML (AutoML, 2022; Azure, 2022) is introduced to automatise the ML process. In this direction, MLOps (MLOps, 2022) paves the way to apply agile methodologies in ML-model development, which can contribute to faster development cycles. Although the mentioned research from the literature provides unique approaches and solutions for the practical application of machine learning, the adaption of frameworks to EEM is still missing.

Figure 1 shows the relation of previous frameworks to EEM. These relations are used for developing the approach of this research. Among all the data science frameworks, CRISP-DM has a more structured way for the application to EEM. On top of data science frameworks, business understanding of the manufacturing processes and domain knowledge for increasing energy efficiency are added to this approach.

3. Research approach

Figure 2 demonstrates an overview of the research approach. To establish the approach of this research for increasing energy efficiency in manufacturing through ML, the initial focus is to understand the manufacturing processes and their challenges. Here, research methods are case studies and brainstorming sessions (workshops) with manufacturers of the process industries. Research projects with three companies in the processing sector, interviews with their plant employees and management, as well as several meetings were held (Alvela Nieto et al., 2019, 2021). The challenges for reaching energy efficiency in manufacturing are extracted and reported in section 1.
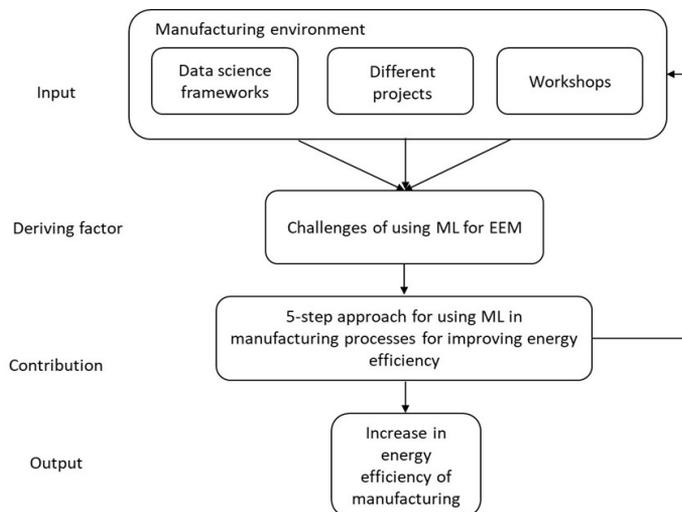

Figure 2. Research approach.

The research approach to design the 5-steps was constructed partly from state of the art and partly from industrial projects. Each of the five-step involves several technical challenges for the application of ML, namely, reaching the goal of reducing the specific energy consumption of a manufacturing process while preserving the quality of the end product. The major technical challenges of ML for EEM to reach this goal are reported within each of the five steps in the next sections. While considering the technical challenges of ML, this paper provides examples of a possible solution to each technical challenge in section 4.

4. 5-steps approach to the implementation of ML methods for improving energy efficiency in processes

Many of the data science frameworks presented in section 3 deal exclusively with specific steps shown in Figure 3, such as steps 2 -"data integration", step 3 -"modelling", and step 4 -"optimisation". These frameworks are integrated into the 5-step approach presented in this paper. However, they require an extension to address application-specific challenges and a continuous improvement of the manufacturing process based on production data. In this research, the 5-step approach additionally contains the steps "process mapping" and "process control" and their challenges. These two steps are crucial to enable a successful and goal-oriented application of ML in interaction with manufacturing processes.

The approach for the improvement of energy efficiency with details of the 5-steps is shown in Figure 3. The topics mentioned in this figure will be presented in the following subsections. In each step, the respective technical challenges during realisation are shown in the tabular format. Knowing challenges and solutions provides a guideline for data science engineers to derive knowledge from data, adjust the process settings, and help manufacturers to better control the process steps during the creation of a product.

4.1. Step 1: process mapping

Current processes of manufacturing can be highly complex. Process mapping is of great importance to reach the maximum possible reduction in energy costs and increase the overall sustainability. As Figure 3 shows, in the process mapping phase, analysis of the current conditions and settings of established processes, objectives
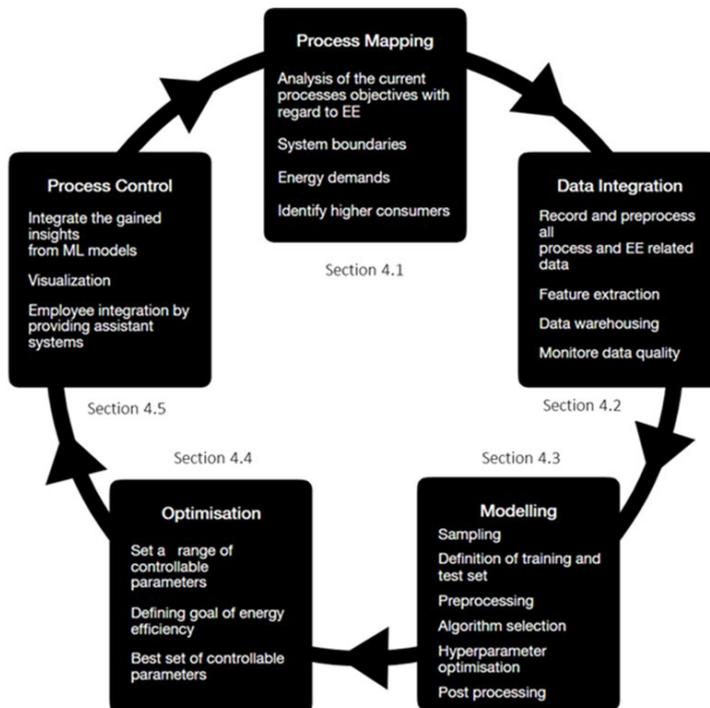

Figure 3. Overview of 5-steps approach for increasing energy efficiency in manufacturing industries.

concerning energy efficiency, system boundaries and detailed analysis of current energy consumption as well as identification of higher energy consumers in a manufacturing plant are investigated. In the case of process boundaries, both individual machines or individual process sections and, in some cases, entire production processes are considered. The selection of process boundary is dependent on the scope of use cases. Energy efficiency improvement by maintenance, changing the parts or changing the production planning is out of the scope of this paper. For increasing energy efficiency and keeping quality at the same level, developing an understanding of the established manufacturing system, connections of the process settings to the quality of product, requirements on product quality (customer side) and opportunities for improving the process quality concerning energy, need to be further detailed and documented. For example, changing specific process parameters of a manufacturing process lead to an increase in energy efficiency, but this increase in parallel causes a decrease in product quality. The knowledge about relevant parameters, criteria in product quality and other standards have to be investigated in the process mapping phase by communication with process experts. The next step, data integration, can be started on this basis, and several improvements can be archived via different approaches like parameter optimisation and energy transparency techniques.

Table 1 shows significant mapping aspects of manufacturing processes for energy efficiency. Along with these aspects, technical challenges are presented.

Table 1. Aspects and challenges of process mapping for increasing energy efficiency.

Aspect	Method–application	Technical challenge
Analysis of current processes regarding EE	Experts interview	Complex production setting, asking the right questions, working language, different viewpoints on the same problems
Identify higher consumers	Value-stream analysis	Processes or machines which consume the most energy
Illustration of material and energy flows in machinery, manufacturing equipment and plant	Process flow diagram (flowsheet)	Recognise all essential aspects, collection of energy consumption from different processes or machinery, which are not aggregated (combined) not available. Energy measurements should first be collected, and later combined together.
Need for a software framework that builds the connection between process mapping, data integration and modelling	Swagger	Collection of all required data sources, early recognition of data structure, need for having an overview and shortcut to remember complexities of the process during ML model development.

Firstly, process and product quality requirements and the effect of these requirements on energy consumption can be partly identified through interviews with experts and manufacturing employees. However, technical challenges such as the lack of an ordinary working language can make the current understanding situation difficult. In some cases, complex interrelations in the production settings make it even more difficult to understand the situation.

Secondly, identification of the essential processes, which consume energy is a necessary aspect of energy optimisation. This aspect influences a productive and effective model development for reaching energy efficiency. Value stream analysis can be used as a tool for this aim (Darwish et al., 2010). Next, illustration of energy streams through process flow diagrams can help to document and quantify the energy flows. However, practical applications showed the authors that energy values are often not available at all. Even when data are collected regarding energy consumption, the values are not available at the detailed level for each individual energy process.

For determining the energy usage, the energy consumption can be calculated per unit of end product at the specified manufacturing process. Considering this approach, it can also handle shared production steps that share their capacity to different lines. For each product or product quantity, the energy consumption for each production step is calculated or measured. After completing the identification of high-energy-consuming processes, energy flows and the amounts of energy, there is a need to dynamically feed the complexities of the process to the next steps. This paper suggests the open-source framework Swagger (Swagger, 2020), see Table 1. This connector can link and document the flow of information between process mapping, data integration and data modelling. Also, HTTP web services (Roy & Ramanujan, 2001) can be designed for this aim. The data structures, which are documented from step "process mapping" can be transferred to "data integration" and "data modelling" using Swagger as an interface description language.

4.2. Step 2: data integration

If the underlying process is sufficiently well understood, it can often be observed that a large amount of data needs to be recorded to describe it completely. Data integration aims to ensure that all process-relevant data is recorded, pre-processed, and provided with the appropriate frequency and quality.

Energy-related data in a manufacturing process can be electricity, water vapour or fossil fuel consumption. Other data that affect manufacturing energy consumption are properties of machinery and processes, such as, motor performance and machine utilisation rate. Besides, data that affect the quality of input material and an end product can contribute to the rate of energy consumption. Moreover, the manufacturing process and external influences, such as raw material variations, affect energy consumption. For collecting this energy-related data from manufacturing, sensors and flow meters can be used (Table 2).

As stated in this Table, determining the number of sensors installed on the machinery and finding the suitable data collection method from manufacturing processes are among the technical challenges that should be addressed during data collection for EEM. Moreover, sensor fusion should be determined, e.g. how to integrate sensors in machinery or processes and where to locate them.

Apart from the selection of a type of data repository (e.g., relational database, energy cloud system (Schaefer et al., 2021), there are some tasks, which belong to the integration phase. See Table 2 for more information.

Using experts with domain knowledge in manufacturing can support tremendously in deciding on energy-related problems and required data features.

Table 2. Aspects and technical challenges of data integration.

Aspect	Method-application	Technical challenge
Collect energy data from machinery and process	Sensors, flow meters, NIR devices	How many sensors, costs, sensor fusion problems
Automatic exchange of data from shop floor to database	Exchange technologies	Need for selection of right tool, standard interfaces, data fetching intervals and size
Store business and energy-related data	Databases, cloud storage	Incompatible data formats, need for controlling data quality, difficulty of recalling data to local computers
Select representative data views	Data tables	Need for domain knowledge, expert interview, energy-related problems, and their scope
Data quality monitoring	Outlier detection in the databases	Dirty data
Communication between devices	Machine-to-machine communication protocols, reading data from devices	Server shutdowns, difficulty of automatic data extraction

4.2.1. Data quality

Having data with superior quality plays an unneglectable role in getting appropriate results from ML models. Firstly, there are standards, such as ISO/IEC 25012:2008 (International Organization for Standardization, 2008) and ISO 8000-63 (International Organization for Standardization, 2019), which provide comprehensive guidelines for the characteristics of data in databases and data integration.

In manufacturing processes, controlling the quality of recorded data from sensors in a database is a significant task. The required information can be not recorded into the database during data collection. In the following, some of the disorders, which can happen in the databases or the related data collection devices are mentioned. In the case of a sensor failure, the sensors may send erroneous data or even no data back to the databases. Similarly, a defect in information transmission compliance, such as Wi-Fi or the respecting battery can cause a disturbance in feeding data in ML models. For example, in case a temperature sensor is not sending data, and the temperature data are fed automatically to a prediction model, this stoppage of recording information from the sensor won't be detected unless a specific mechanism is designed to detect this disorder in information transmission. Another case is the unexpected shut down of servers, which can cause an interruption in saving correct data to the database. Therefore, mechanisms such as outlier detection are needed to consistently check the quality of data (Table 2). As an example of a solution regarding outlier detection, see Scikit Learn (2007).

4.3. Step 3: modelling with machine learning

Machine learning algorithms can lead to pattern derivation from existing datasets without being explicitly programmed (Monostori, 2003). These patterns and respective information can support manufacturers in

decision-making, to better understand manufacturing processes, and to have higher transparency of energy consumption in processes. Therefore, the step of modelling and in particular, the selection of an ML model as well as input variables are important. The core feature is that ML models learn from past data to generalise into the future. In this paper, ML models consider the best set of controllable process variables for less energy consumption while the quality of the produced product is maintained at the expected level. For this, Figure 4 presents a data-driven modelling approach based on product and process data.

Above all, the volume, variety and velocity of data collections pose a big challenge in the modelling and, therefore in the selection of an ML-model (Sen et al., 2016). There is thus a close link between the step "Data integration" and the step "Modelling". Usually, one realises data problems while modelling or gets ideas when collecting new data. For the presented modelling approach in Figure 4, variables related to the features of the process and product are selected. This can be done automatically or semi-automatically under the guidance of an expert (Goodfellow et al., 2016). Choosing features of a product, such as an edge, and rejecting its colour is a kind of feature selection. Identifying and removing irrelevant and redundant features reduce the dimensionality of data and enable ML to operate faster and more effectively (Yu & Liu, 2004). Such exemplary sensor signals of a particular product type, whose main characteristics (features of the product type) will be kept whilst unnecessary correlations are discarded.
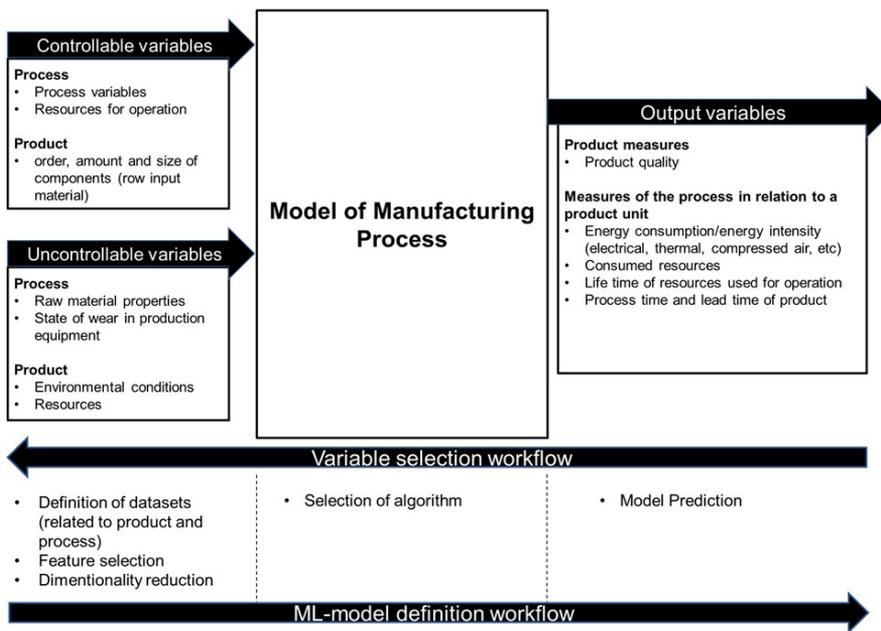

Figure 4. General data-driven modelling approach for manufacturing processes.

4.3.1. General data-driven machine learning modelling for manufacturing

There are no models based on physical principles for many interrelationships in manufacturing plants, but an extensive database is available in many cases. For these models, a uniform approach to model the product behaviour in the underlying manufacturing process is presented in Figure 4. This model is one of the contributions of this paper.

Figure 4 views a manufacturing process from a data-driven perspective, which covers product and process information. The influences are categorised into different input and output groups. The goal of this data-driven modelling approach is the possible application of ML methods, and their use the increased energy efficiency. The input on the left side of Figure 4 is divided into controllable and uncontrollable parameters. Parameters are seen as variables in this data-driven model. All variables that can be actively changed during the processing of a product are called controllable variables. The variables, which cannot be actively influenced but are measurable and are used as information sources within the model, are called uncontrollable variables. This representation is based on an approach from statistical experimental design (Kleppmann, 2016).

For the use of this generalised modelling approach in presenting the process behaviour to reduce the energy consumption while conserving the quality of the product, both product quality and process quality need to be part of the output variables of the model. In this way, the influence of the input variables on the outputs can be learned based on manufacturing data. All relevant information that affects the outputs must be covered within the input variables (controllable or uncontrollable). Otherwise, it won't be possible to train an accurate model. The model's performance is a key factor of this approach and the following steps of the proposed framework. If the model performance is insufficient, the next steps like optimisation or process control cannot positively affect the energy efficiency of the manufacturing process.

The model of the manufacturing process (as shown in the middle of Figure 4) can be a pure prediction model as well as a basis for an optimisation process. As a result of an optimisation, more favourable settings for the control variables can be proposed. However, this requires measures to be defined based on the output values, e.g. a cost function for the optimisation process.

Further, selecting an accurate ML algorithm for a given problem is not simple. Numerous methods of ML have been suggested for the creation of classification models. Yet, there is no clear picture of which method is the best for which task in manufacturing (Vilalta & Drissi, 2002). One possible approach is estimating the accuracy of the ML candidates' algorithms and selecting the one that seems to be most accurate. Moreover, experiences gained during projects about the use of ML algorithms for EEM show that, in general, all machine learning methods that can model regression problems are used to model the product behaviour within the manufacturing process (Alvela Nieto et al., 2019).

Practical experiences and characteristics of the selection of ML algorithms as a result of a series of implementations and their deployment in accurate manufacturing for achieving efficient processes in terms of energy have been summarised in (Alvela Nieto et al., 2019). Table 3 shows the applied ML algorithms in real manufacturing environments that have been selected for modelling the product behaviour in a particular process (Figure 4).

Table 3. Aspects and challenges of data modelling.

Aspect	ML algorithm	Technical challenge
Product or process features	Support Vector Machine (classification)	Parameter settings, labelled data
Product or process features	K-Means (clustering)	Data dimensionality, parameter settings, unlabelled data
Continuous or class-like outputs	Neural Networks (regression or classification)	Relevant features, overfitting, multiple outputs, labelled data
Continuous outputs	Support Vector Regression (Regression)	Relevant features, overfitting, labelled data

4.4. Step 4: optimisation

If an accurate machine-learned model has been trained, optimisation can be used to map a manufacturing behaviour for the output variables. To realise the effect of input variables (controllable and uncontrollable, see Figure 4) on the behaviour of the manufacturing process, the controllable variables need to be changed. In what way these change needs to be performed shall be determined within the optimisation step. First, one must decide, which set of controllable variables shall be actively changed in which ranges. Second, the optimisation goal needs to be defined. This goal can be constructed in any way from the output variables of the model (Figure 4).

The optimisation goal needs to be expressed in a single optimisation rating. Following the optimiser's strategy to achieve a maximum/minimum optimisation rating, the chosen set of controllable process variables is changed. At the end of the optimisation step, the output is the best set of controllable variables. This set can be used as a proposal for more energy-efficient manufacturing.

A major technical challenge in optimisation is that most machine learning methods have the disadvantage that they are black-box models. Only the input and output of the model are visible. The way to calculate the output can hardly be represented transparently and is rarely mathematically described in the form conventional optimisers can handle. For this reason, optimisation procedures that can process black-box models are necessary. Evolutionary algorithms can be used as an example of this. Table 4 shows optimisation algorithms that can be used in this step.

4.5. Step 5: process control

Process control aims to integrate the gained insights from ML models within the process. In this paper, the applicability and benefits of this new knowledge underline the improvement of energy efficiency in manufacturing.

Table 4. Optimisation for energy efficiency.

Aspect	Method–Task	Technical challenge
Optimise process variables	Evolutionary algorithms	Not visible (black-box), the range of variable combinations needs to be noted, unknown variable combinations
	Grid search	Same as evolutionary algorithms, additionally computation time growth with high-dimensional optimisation variable grids

This may mean a formal integration, such as a model forecasting that is then read and visualised. Alternatively, this may be using the gained knowledge to elicit changes in the organisation. On the one hand, the new insights as recommendations can be presented to employees and managers through assistant systems to better select process settings in the form of visualisations. Hence, this can support decision-makers in operational processes and reduce energy consumption. On the other hand, discovering patterns in the data indicating, i.e., new behaviour in energy consumption, may not be formally integrated into the assistant system. Still, it will be helpful in visualisation for planning and decision-making at the management level.

4.5.1. Employee integration by providing assistant systems

Visualising the findings made during the application of ML in manufacturing processes can give the operator additional information about good or bad production patterns for production outputs, such as product quality or energy consumption. The operator then has to learn by itself the relationships and adapts process parameters differently. In other cases, energy-efficient parameter patterns suggested in optimisation have to be adjusted directly into the process control.

A different way would be to propose a process pattern, which has to get accepted by an operator. This has the advantage that the operator does not need to extract optimal process parameters for every situation (dependent on weather, material and so on) on his own. The optimal solution is created based on the machine-learned model during the phase of optimisation. But the operator still has the chance to prevent misleading process behaviour in case of wrong patterns. This increases the safety of the process in comparison to direct feedback to the process control. Technical solutions for the communication between machine-learning framework and process control can be OPC (OPC Foundation, 2020) and REST interfaces (Daigneau, 2012). Employee integration by providing assistant systems is a better way to try out the correctness of the process patterns proposed by this 5-step approach.

Including the operator's skills and conditions in the assistant systems can also improve the performance of this system for energy monitoring and optimisation. The interested reader can get more insights by referring to (Botelho et al., 2014).

5. Application scenario

A scenario for applying the 5-step approach is a process step from animal feed production. For this purpose, an energy-intensive process step is described, which ensures the grinding of grain into flour in a so-called hammer mill. A hammer mill is a machine, which shreds the grain in the plant.

Step 1: Process mapping. In step 1, with the help of the tools presented (see Table 1), the specifications of the process and improvement areas are identified. During the process of shredding grains with the hammer mill, the granularity of the output flour is important for usability and, ultimately, animal health. Therefore, the granularity of flour is a key product quality characteristic. Next, parameters (variables) that influence this process and boundary conditions for this manufacturing process are identified. A brief selection of parameters is shown in Figure 5. The findings after analysis of the process and interview with the experts at the factory show that one of the most important parameters of the hammer mill is the rotor speed. If its value becomes higher, the crushing degree of gains (product quality) increases, while the electrical energy consumption increases as well. Therefore, this 5-steps approach should aim to decrease energy consumption depending on the quality and nature of the grain speed (disturbance variables), at the same time preserving the flour quality by suggesting optimal settings for the rotation speed of the mill (process parameters). See subsection 4.3.1 and Figure 4 for more information about defining the general data-driven modelling.

Step 2 Data integration. In the data integration step as described in section 4.2, the necessary database for describing the process was recorded using the approaches of the framework (see Table 2).
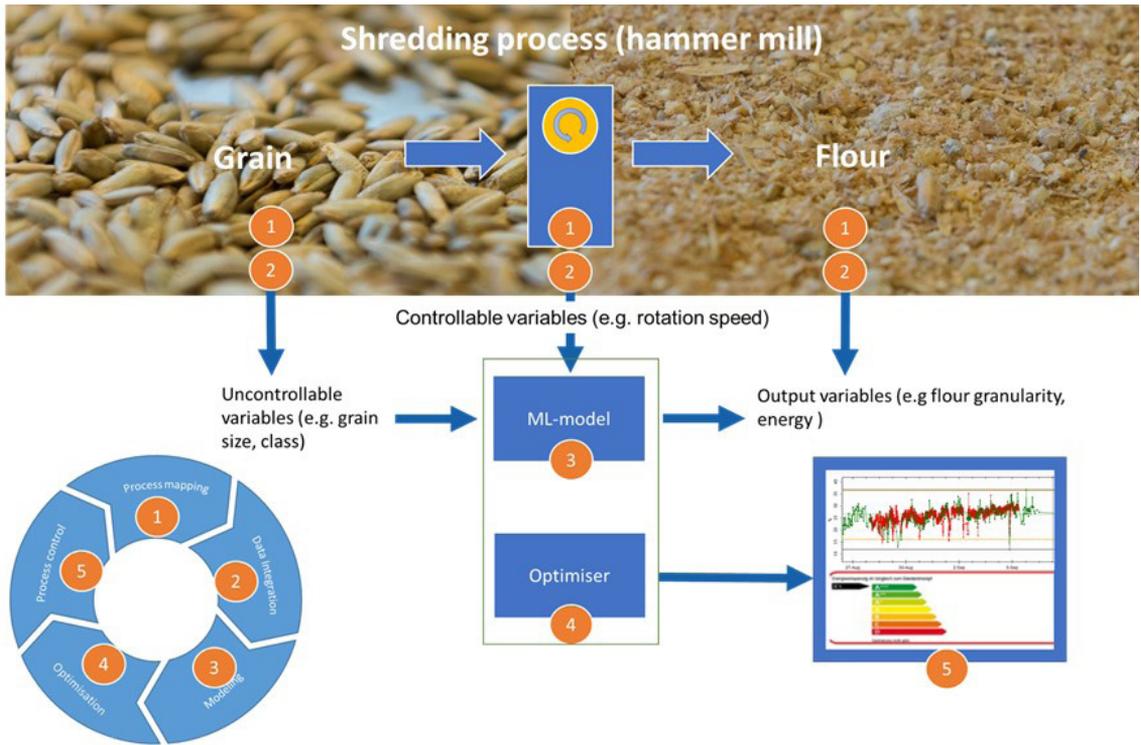
Figure 5. Overview of use-case in feed production.

Step 3 Modelling. With a neural network, the model context was modelled based on data for the identified output variables. More information about ML modelling was given in section 4.3.

Step 4 Optimisation. In combination with the model, an evolutionary optimisation algorithm was created that optimally fulfils the optimisation goal (see section 4.4) identified in step 1 about energy efficiency and product quality. The result of this step is the suggestion of an efficient rotation speed at the hammer mill.

Step 5 Process control. As described in the framework (see section 4.5), the suggestion for the speed from step 4 can be made available visually for the employee or transferred directly to the process control via a REST interface.

By carrying out the 5-steps according to the procedure presented, the defined goal for the process of shredding can be carried out more energy-efficiently with producing the same flour quality. Structuring the necessary work in these 5-steps means that the activities are easier to understand for the company and can be carried out more quickly. The actions made are visually presented in Figure 5.

6. Discussion

In the first part of this section, the paper provides an evaluation of the 5-steps framework, and in the second part, a discussion on the generalisability of this 5-steps approach is provided.

6.1. To what extent can overcoming the technical challenges of ML contribute to reducing the problems of manufacturing for improving energy efficiency?

For a better evaluation and clearance of the mentioned 5-steps approach, the challenges to EEM are summarised in Table 5, and the 5-step approach identifies opportunities to overcome them. Table 5 covers the challenges of manufacturers, which were previously mentioned in the introduction (section 1). The potential solutions to these challenges are originated from the 5-steps framework (section 4) and shown in the column "Suggestions".

Table 5. Challenges and opportunities to energy efficiency in manufacturing processes.

No.	Challenges	Suggestions
1	Lack of transparency of energy use	Identification of value-adding and non-value-adding processes, illustration of material and energy flows, identifying higher energy consumers (step 1 - "Process mapping")
		Using data tools and interfaces for measuring energy, collect data in a structured form (step 2 - "Data integration")
		Identifying variables of process and product that affect energy consumption through a data-driven modelling view (step 3 - "Modelling")
		Visualisation of energy-saving opportunities for key energy drivers and process settings (step 5 - "Process control")
2	Need for structured product and process-related data	Data collection through sensors, flow meters, camera devices, using data technologies such as database, swagger for data storage and linkage between them (step 2 - "Data integration")
		Automatic data transfer and exchange through protocols, data quality monitoring (step 2 - "Data integration")
		Structuring employee's knowledge about the product quality process configurations through interviews, Swagger (step 1 - "Process mapping")
3	Lack of reliability of employees to the robustness of sensor values or automated measurement systems	System for monitoring the accuracy of measurements (step 5 - "Process control")
4	Adapt to future digitalisation and automating manufacturing process	Assistant systems (step 5 - "Process control")
		Continuous learning (update) of deployed models (step 3 - "Modelling", step 4 - "Optimisation", step 5 - "Process control")

Based on the results in Table 5, if the challenge of "lack of transparency of energy use in a manufacturing" is observed, identifying processes or machinery, which have high energy consumption, using proper energy measurement devices, using interfaces (e.g. Swagger) for linking collected data in a structured form, providing visualisations of energy flow for machinery and processes are needed to overcome this challenge. For more suggestions, please see Table 1 and Table 2.

The challenge "Need for structured product and process-related data" has been addressed in steps 1 and 2. Structuring the knowledge of processes through interviews with the experienced employee, embedding sensors and flow meters on the machinery, database systems, and data quality control are the suggested methods for structuring product and process data.

For "increasing the reliability of employee to the robustness of sensor values or automated measurement systems", the 5-steps can allow the manufacturer to optimise the settings of machine or process parameters to reduce energy consumption. Further, employees can learn the variations in the process parameters better after they use the suggestions on process parameters from ML systems. By optimising processes via machine learning (for improving energy efficiency), they may need methodological expertise in data science, ML, IT competencies for data collection, provision and return, and well-defined use-cases. These requirements are addressed in this paper's concept, section 4, for improving energy efficiency within 5-steps.

Finally, the challenge "Adapt to future digitalisation and automating manufacturing process" is realised through the deployment of machine learning models in the manufacturing process and supporting the employee with assistant systems. This approach can suggest the best combination of process parameters, which optimises the energy consumption and at the same time keeps the quality of the end product unchanged (see Figure 4, section 4.5).

6.2. Generalisation of findings to other manufacturing

The presented 5-step guideline is already tested on processes in research projects (Alvela Nieto et al., 2019). The results showed that there is a difference in the level of maturity within 5-steps. Some of the steps are newly developed and should be tested more (e.g., ML modelling view). Some are well defined and generalisable to other processes (e.g., swagger). Representation of variable to controllable and uncontrollable, and decision on these groupings should also be tested more in future. There is still no magical ML algorithm that solves all problems

of manufacturing processes. The selection of algorithms is very case-specific and depends on the availability of data and the technology used for each situation.

The use cases of the 5-step guideline were based on SME manufacturing. Thus, the generalisability to other SMEs processes or other manufacturing branches should be considered in future research.

7. Conclusion

This paper presents a 5-step approach for using data from manufacturing environments with ML algorithms to improve the energy efficiency of processes. The 5-steps are explained and the deployment of energy measures through ML is discussed by presenting challenges. Essential aspects for reaching EEM were mentioned and solutions were suggested. This research gives an overview of reaching energy efficiency in manufacturing and how the application of machine learning help in quantifying energy efficiency challenges. Additionally, the application of the 5-steps approach is implemented in a process step. Future work for completing the 5-steps to make them even more beneficial in manufacturing can be, to research the topic of explainable ML models and continuous learning, as well as providing the employee and management with a better interaction with the machine learning models through a straightforward explanation of changes in the processes and their effects on the quality of the product.

Acknowledgements

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