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Assessing Energy Efficiency in Processes of the Agri-Food Sector: From Delivery of Natural Resources to Finished Products

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Abstract. The agri-food sector accounts for 26% of the EU energy consumption, where 28% of this energy belongs to natural resource processing. As multiple products are produced on the same line and numerous process steps are interrelated, the energy use in this industry is complex in general. Moreover, bottom-up data analysis of how much energy processes are used, and furthermore, why and where opportunities for improvements exist, are less prevalent. This paper proposes a methodology for estimating the energy consumption of the agri-food processing. The collection of real data from several industrial enterprises in Germany as part of research programs enabled an accurate assessment of energy consumption and savings.

Keywords: Energy Efficiency · Agri-Food Sector · Product

1 Introduction

Efficient energy use is one of the basic requirements for the future of the agri-food sector, more so since, with the recent increase in energy prices, it is important to boost global food production, which is highly dependent on the use of energy, mainly electrical and fuel energy [5]. Energy is used throughout the agri-food supply chain, starting from the production and use of agricultural inputs and then moving to processing, packaging, and distribution to the customer. In the EU, alone the natural resource processing accounts for 28 % of the total agri-food sector energy [3].

Small and medium-sized companies (SME) allocate the majority of the fuel energy, namely natural gas, across production processes in the food processing phase (up to 85 %) [9]. On the other side, the energy percentage of auxiliary processes (also called support processes) is typically assumed to be lower and mainly electric [7][9]. On average, the use of lighting, compressed air production and cooling is pure electric [9]. A production process, such as grinding and mixing, is more heterogeneous across companies than auxiliary processes, directly related to the core business, and managed mainly by production managers [2]. Auxiliary processes, on the other hand, are those which maintain the

manufacturing activities but do not result in products as such (e.g., ventilation, pumping). Food is typically produced in batches (product lots) in this sector, and each batch’s energy requirements for bringing it ”from natural resource to fork” varies greatly from the next. Even when analyzing the same product type, its energy ”cost” can differ notably, reflecting the low efficiency of production processes as a result of changing resource properties (owing to cultivation, farming practices, etc.) [10].

The overall goal of this study is to enable companies to make a robust statement about the specific energy consumption (SEC) of each individual batch. Key process parameters are frequently not paired with the properties of food resources due to their stochastic character. Incorporating these key batch characteristics into the energy analysis can allow for a precise evaluation of the product quality in terms of energy consumption. In line with authors’ previous works and research projects [1][2], production processes were examined using a methodology based on machine learning (ML) and historical data about process conditions, product characteristics and energy values, without any investments in (new) efficient equipment. Unless stated otherwise, the estimation of energy consumed by a batch in this work includes the required process energy from the delivery of natural resources (raw material) until the production of a finished product, excluding logistic and auxiliary systems. On the project experiences and results, this study contributes to developing a methodology for estimating energy consumption through a validation of process operating conditions as a means of product quality improvements.

2 Methodology for Estimating the Energy Consumption of Agri-Food Processes

Energy efficient improvements are defined as increasing the output per unit of energy used, resulting in energy savings if the output does not change [4]. In the industrial sector, it can mean getting the most out of every unit of energy it is bought [4]. Therefore, an increase in energy efficiency (EE) can be realized by actions, e.g., technical or technological actions, seeking to save energy without altering the product quality. In the agri-food sector, particularly, processes that are energy-intensive vary by sub-sector (e.g., cereals, sugar, coffee, etc.). For instance, milling and centrifuges in sugar processing and grain milling in the ingredients sector use the most electrical energy [3]. Most of these processes rely on electric motor systems, including steam systems, pumps and compressors, and also heating, cooling and refrigeration systems. While not exclusively, most opportunities to EE in this segment of the food sector come from measuring the demand for electrical and thermal energy [8].

Previous studies use different accounting methods, and system boundary conditions which result in a large range of specific values where steps, processes and product properties were mostly unknown [5]. Equipment details were rarely provided, and the processes included were often not mentioned. These unaccountable factors could have a large impact on the values of the process energy

obtained. A complete energy evaluation of the processing stage should start with the delivery of resources, including pre-storing, and should finalize by wrapping and post-storing. However, data at high granularity are not overall acquired. The focus of this study thus lies on the processing line, excluding wrapping, storing, and auxiliary processes. Any variations of a production process line are costly and not as easily accomplished as it is, e.g., changing the lighting in an industrial facility. To make it apparent, which processes are being studied, the entire agri-food processing segment can be split into three stages (see Figure 1): **S0**: Storing and preparation of raw materials according to the production requirements before the production line.

S1: Processing of raw materials on the production line.

S2: Product wrapping and storing before shipment.

Stage 1 (S1) has indeed the most significant impact on specific energy consumption because they are usually connected to thermal processes [5]. Stages 0 and 2 thus are out of the scope of this study. It is convenient to use a methodology that comprises the natural resource processing (e.g. one or more machines or production lines) for an accurate calculation of the required energy to a certain products batch, as well as it is applicable to various sub-sectors and batch qualities (e.g. multiple products passing through the same line or single machine). The assessment of energy efficiency is to be understood as the ratio of batch size out to the energy input. From these settings, energy efficiency can be achieved with the help of data-driven models based on ML methods [1]. Then a view of the process design and data sources related to the production process and batch characteristics (raw materials) is of importance. In addition, the term SEC defined by [6] is required as an instrument to capture the amount of energy used by an (intermediate) product at each process step. Hence, the successful application of the methodology depends on the continuous measurability and availability of SEC ($e_1, .. e_n$) in a timely manner. The allocation and aggregation of SEC ($e = e_1 + .. + e_n$) along a production process ($p_1 .. p_n$) expresses the embodied energy of a finished product quantity e_{emb} associated with the processing phase S1 (see Figure 1).

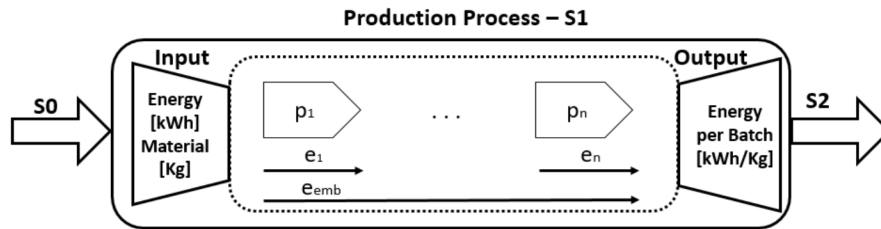


Fig. 1. Energy analysis of a production process at S1.

The proposed methodology for estimating the embodied energy is derived from works on research projects within the food segment. As visualized in Figure 2, the methodology is characterized by two parallel processes, which interact with each other during the entire development period. The design process focuses on determining the specific energy by following a predefined series of necessary steps. Specific energy data can be collected based on process-based metrics, where energy input in kilowatt per hour (kWh) is divided by product output quantity, e.g., in tonnes (t). Energy values expressed in different units are to be converted when possible. This format provides a consistent (and comparative) basis. Simultaneously, the data sourcing process consider the analysis of data with regards to availability, collection and storage. Indeed, data collections are categorized depending on the aim of the process. For example, data about conveyor systems are, as mentioned before, not included in the energy analysis. Each of the production process steps in S1 has to be connected to meter units. To reduce inaccuracies on energy values, unit conversions of raw data, such as process data, should be manipulated as little as possible.

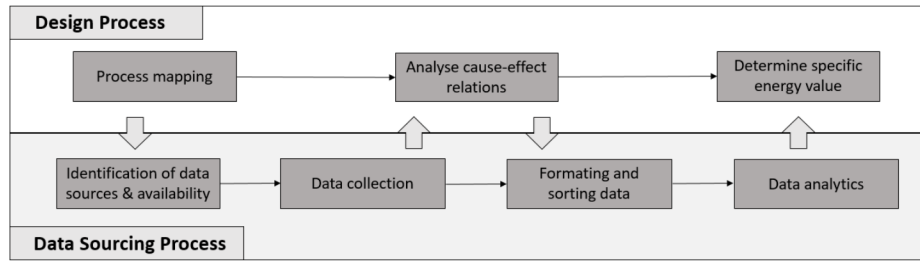


Fig. 2. Methodology.

Hence, the first step contains the analysis of system boundaries, which processes are support processes and which are not. For example, support processes can be divided into ten categories, including ventilation, internal transport and cooling [9]. However, the array of processes under the term support processes has to be carefully examined. Then, for instance, pumping and compressed air are difficult to exclude from production processes in some industries. Further, this study corresponds to the individual industrial sites of SMEs, and thus transport and logistics across different company facilities are not applicable. Next, objectives concerning energy efficiency and current operating conditions, such as reducing thermal energy values, are to be defined. Most of the requirements to product and process quality can be identified and better understood through interviews with plant-side experts. In the next step, it is crucial to analyze and understand the underlying cause-effect relationships as well as interdependencies between process steps and their effects on energy consumption. Many factors that can happen during a production process have to be taken into account, e.g.

fluctuating quality resources and/or operating conditions. For instance, when a cheese type ripens longer than 14 days, the specific energy demand can increase up to 65% [5]. Therefore, process variables need to be defined and measured (i.e. room temperature, humidity), representing key process parameters and reflecting the cause and effect relations of the cheese quality. A close look into the data sourcing is essential as data availability and measurability for such parameters are prerequisites. As mentioned, processes depend on many factors, and even under the same conditions, the energy consumption can differ from product to product because of the changing properties of natural resources. In our studies, the estimation of consumed energy of the part of the product life cycle from the crops delivery to the shipment as flour (as a finished product) was compared. In early summer, a product was produced in a certain production line. Three months later, the same product with the same predefined quality was made in the same production line; only the time frame of crop harvesting differed. Flour belonging to earlier summer consumed 6,5% (91,41 kWh/t) lower energy than flour from later summer (102,11 kWh/t). Considering these data and the fact that the flour was produced in the same way regardless of the date of harvesting (or time of storing), it can be said that the time of harvesting (due to weather events) or storage significantly affects the intrinsic properties of the cereal and thus the consumed energy of a process.

In order to include the influence of product quality characteristics on the process consumed energy, information about the product properties is to be added into the energy analysis. Drying potatoes, as a further example from the research projects, consumes large amounts of energy due to the high initial water content as raw material. The level of water content are thus to be captured and included in the energy estimation. On the basis of all preliminary assessments, the analysis of energy required by a process should be performed. In total, relevant characteristic data should correspond to the production processes that are stored in the databases, e.g., motor speed rates, etc. But also key characteristic data of the product, which are not changeable, such as moisture or starch. The latter are uncontrollable and product-specific variables whose values have to be considered for precise energy estimation. It is evident that methodologies that deal with the complexity and wide range of unstructured data, and their volume, synergistically benefiting from them, are required. Data of process and product can contain valuable insights on where, how and why along process energy values from batch to batch fluctuate. Moving from pure quantitative models to ML, that can limit energy values and maximize quality, can support manufacturers in estimating their specific energy demands for particular resource characteristics and quality specifications. Particularly, the modeling of physical correlations between process settings and quality criteria can be used to characterize and thus optimize the impact of operational decisions on energy consumption, on the one hand. On the other hand, the influence of changing material quality characteristics on the quality of the finished products batch can be better understood in terms of process consumed energy.

3 Discussion

The methodology of this paper was evaluated in multiple settings and sub-sectors of the agri-food segment [1]. Hence, it is not tailored to specific sub-sectors or production processes. Nevertheless, the identification of energy consumption trends was difficult, as the agri-food processing industry is very fragmented, products are processed to varying degrees, and production is not always continuous.

Allocation of energy consumption: The data collections showed that, notably in the ingredients sector, the production processes accounted for the majority of the consumed energy, with thermal processes alone accounting for about 60-70 % percent of spent energy. From the study, it was also noted that fossil fuels (gas) are the primary source of thermal energy, which is mostly used for drying or sterilizing. Further, the data across sub-sectors demonstrated that the more energy-intensive and smaller a company is, the more difficult it is to distinguish the energy values from production and auxiliary operations. From the SMEs case studies [1], results revealed that auxiliary processes consume up to 40 % energy on average. This figure outweighs what has been previously calculated by previous research (i.e. [9]), what may pose unexploited potential in energy-intensive SMEs.

Energy efficiency potential: From the literature, the majority of the energy-efficient measures for SMEs are proposed for generic auxiliary processes. These measures are mainly related to replacing ventilation, reducing space heating, etc.[9]. Our findings across sub-sectors suggested that production processes can lower their consumed energy by 30 - 35 %. This is reasonable, especially in case of no "state of the art" equipment. Further, a factor which seemed to affect positively the energy efficiency of a process is the level of capacity (as total mass): The more natural resources are processed at once, the less embodied energy is allocated to a batch.

Moreover, this study only addressed the theoretical energy-efficient potential of production processes in terms of operating conditions through historical product and process data. The real potential is only achieved if 1) Data quality and granularity are sufficient, 2) All measures derived from the data analysis with ML are implemented. Derived measures can be, for instance, an adjustment of process operating conditions under changing resource characteristics. Further, auxiliary processes should also be considered in the embodied energy calculation with a factor of 0.4. However, the calculation of this factor should be further investigated, as it might vary up to the sub-sector.

Limitations of methodology: This study only accounted for the electrical and thermal energy use of production processes. Many feed and food products have a processing phase that involves energy use at specific processing stages (e.g., grinding) plus energy usage related to intensive internal transportation or other intermediate inputs that ultimately go into a finished product. The additional consumed energy values should be added to the embodied energy of a product batch. Due to factors such as low diary orders or maintenance breaks, production is not always continuous, therefore idle modes still utilize energy and should be factored into the assessment of embodied energy. Results also showed

that the estimates of energy consumption for the same batch qualities across different seasons revealed significant variances. Consequently, the energy values can only be assigned to individual product batches rather than general feed or food groups.

Measurable product properties data: The supply of data, particularly key product characteristics at each process step at high granularity, can become challenging. At least food processing industries are interested in intrinsic or geometric (so-called physio-chemical) product properties as continuous measurements. Nevertheless, these systems, including cameras, are susceptible to surrounding environments and material flow rates. For instance, sensor calibrations to each (new) product require a unique calibration pattern. Other sensors are not highly sensitive to the product properties, e.g., particle size distribution for flour production. These examples of data acquisition to critical quality attributes prevent obtaining valuable (qualitative and/or quantitative) information from the product, and therefore, data quality can become insufficient.

Machine learning to data analysis:

ML analysis often has more difficult meeting data challenges rather than conventional methods. Data challenges include the amount, quality, and types of data required, among others. Aside from the expert knowledge needed to build these models, the most challenging tasks in realizing successful production data analysis were at the start of the data pipeline, namely, the data acquisition.

4 Conclusions

The assessment of energy efficiency can, of course, not substitute an energy label on a product, such as a carbon footprint label or an energy audit. Still it can act as a preliminary company-internal audit, indicating where a company should focus its efforts. Some methodological improvements, such as the significance of taking into account the consumed energy by auxiliary operations from the implementation, were found to be necessary. Furthermore, this research suggested to incorporate a division between production processes and auxiliary processes. However, a general energy-use taxonomy and standardization would greatly enhance the knowledge of data across the sector. A similar approach to the Nutri-Score could allow customers to compare energy values along the same product qualities, promoting energy efficiency in the agri-food sector. In a long-term scenario, a greater collaborative effort is required to report consumed energy data not only at the processing stage but throughout the food chain.

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