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Modular Energy Demand Modeling of Manufacturing Processes for Energy Efficiency Improvement

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Abstract

The decarbonization of manufacturing processes through energy efficiency is complex due to diverse process requirements and technical interactions between processes. However, to identify energy efficiency potentials systematically transparency about the current energy demand is required. This paper presents a modular modeling approach to classify and determine process-specific energy needs. For the modeling of energy demands, a classification of the manufacturing processes by process modules is implemented. By the introduction of energetic operations, the minimum, assistant and loss energy demand are modeled. The method is applied in a vacuum annealing furnace and in a production line for the assembly of housings. The validation of the furnace shows a 4,85% and of the production line 4% deviation between modeling and measurement of the total energy demand. The energy loss demand amounts to 61,8% for the furnace and 35,86% for the production line, which are the starting points for energy efficiency improvement in further research.

Keywords: Energy efficiency; Energy demand modeling; Manufacturing, Decarbonization

1. Introduction

The urgent need to meet legally binding climate targets, such as the 1.5°C limit set by the United Nations [1], has intensified the focus on strategies for decarbonization across all sectors. The industrial sector, responsible for a significant share of 24% of global greenhouse gas emissions (GHGE) in 2019 [2], plays a pivotal role in these efforts. Energy-related GHGE constitute a major portion of the sector's overall GHGE, making energy efficiency (EE) a critical starting point for decarbonization. However, assessment of advanced EE needs clear understanding of process energy needs and the resulting final energy demands. In this context, this paper investigates the potential of EE improvement (EEI) of manufacturing processes based on a developed approach to model process-specific energy demands modularly as a primary lever for industrial decarbonization. In this context, the generic modeling of energy demands may serve as a crucial foundation for identifying process-specific EE potentials (EEP), which can be quantified using corresponding energy performance indicators (EnPI) [3].

EEI in industrial processes typically unfolds in several phases illustrated in a previous work by the authors [3]. The focus of this study is part of the identification of EEP as the first phase of the holistic approach of EEI including the following steps:

- **Energy data acquisition:** By determining the current technical energy demand (TED), the energy status of the production process and its sub-steps is described [4].
- **EnPI generation**: The generation of EnPI is aimed at the comparability and interpretation of the TED for EEB [5].
- **EEB:** Various benchmarks can be defined to identify the EEP by calculating the difference between the respective benchmark and the current EnPI based on the TED [6].

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Consequently, the determination of the TED is the starting point in the holistic process of EEI. Focusing on the selected case studies (see section 3.1), previous studies investigated following energy demand modeling approaches:

Gajic et al. [7] modeled the energy consumption of an electric arc furnace using neural networks as a function of the annealed material. The approach of calculating energy consumption using machine learning methods and neural networks can also be found in the work of Manojlović et al. [8] or Wang et al. [9]. This is based on comprehensive measurement data from the system under investigation for training the neural network. Zareba et al. [10] use analytical modeling of occurring heat flows and heat loss mechanisms to draw conclusions about the furnace parameters and model parameters in an inverse procedure. Hajaliakbari et al. [11] developed a mathematical model to compute the heat flows of a roller hearth furnace in order to simulatively describe the temperature distribution in the different zones. Sardeshpande et al. [12] pursued the goal of model-based determination of the minimum energy requirement for benchmarking by developing a simulation model for a glass furnace. Hasanuzzaman et al. [13] evaluate the EE of a vacuum annealing furnace by investigating exergy and energy efficiencies and losses.

Due to the high complexity and variability of production lines, either only individual components within the production line are usually considered or an analysis is carried out based on the absolute energy consumption of the system [14]. Dietmair and Verl [14] developed a generic approach for describing the energy demand of production plants based on statistical, discrete state modeling by recording the average performance of the respective system states using typical load profiles for the given plant and multiplying it by the dwell time. Jeon et al. [15] evaluate energy consumption based on measurements at system and production line level or at plant level, and assign it to different products. Su et al. [16] modeled a production line as a Bernoulli chain in order to increase the EE of the production line by minimizing standby times. Seevers et al. Focus on time-series analysis and non-intrusive load monitoring of machine tools to apply EEB [17] and to point out automatic control of energy demands [18].

Considering generic approaches, Sun et al. [19] described a conceptual framework for modeling the TED of manufacturing processes. The authors distinguish between energy that is *necessary* for production, energy that *assists* production and *ineffective* energy demand. Contributing to the necessary energy, Kreitlein [20] introduced the *minimum energy demand*. This describes the part of the system-specific energy demand that is physically necessary to carry out a transformation. To describe the transformation, 15 basic operations (BOP) are defined, which can be used to physically map all manufacturing processes in accordance with DIN 8580. A BOP describes the physical or energetic transformation process and cannot be further subdivided. Thus, it enables to determine the minimum energy requirement which is independent of the selected production method or machine type. The minimum energy requirement can be equated with the physical EE benchmark describing the maximum and theoretical EEP [3].

Despite these advancements, existing energy demand models (EDM) often lack the flexibility and generality needed to accurately assess the EE of diverse manufacturing processes. Current models tend to be either too specific, focusing on particular processes or equipment, or too generic, failing to capture the intricacies of individual production methods. Thus, a gap remains in the generic modeling of the holistic energy demands of individual manufacturing processes. This gap highlights the need for a more adaptable approach to energy demand modeling that can be generically applied across various production environments, while still providing the basis for precise insights into EEP by modeling process-specific energy loss requirements.

This research aims to fill this gap by providing granular and process-specific models that can accurately assess and enhance EE. The novelty of the proposed approach is the methodical extension and specification of previous generic frameworks which contribute to the holistic determination of energy demands. For this purpose, a method is introduced allowing manufacturing processes to be systematically characterized. Finally, the research question is how the TED can be modeled holistically in context of EEI using generic EDMs of manufacturing processes.

The study is structured as follows: section 2 presents the method to develop generic EDM and to determine the TED. In section 3, the method is applied to two case studies. The results are shown and discussed in chapter 4, before the study ends with a conclusion.

Nomenclature

BOP	Basis operation
EE	Energy efficiency
EEB	Energy efficiency benchmarking
EEI	Energy efficiency improvement
EEP	Energy efficiency potential
EDM	Energy demand model
EnPI	Energy performance indicator
COP	Coefficient of performance
GHGE	Greenhouse gas emissions
HCP	Housing creation plant
LOP	Loss operation
PPM	Primary process module
SOP	Side operation
SPM	Secondary process module
TED	Technical energy demand
VAF	Vacuum annealing furnace

2. Method for energy demand modeling

2.1. Structure of energy demand models

A manufacturing process is defined as a sequence of manufacturing steps in which a material or product is transferred from an input state to an output state [21] in accordance with DIN 8580 [22]. This process is referred to as transformation. The manufacturing process takes place within a production environment in which one or more manufacturing processes are carried out and which describes the local production conditions. In addition to Kreitlein [20] a manufacturing step is divided into primary (PPM) and secondary process modules (SPM) within a production method for which the energy demand is modeled (see Figure 1). The term process module describes a separate, functional part of a larger system that performs certain tasks or functions. It is a unit within an overall system that can operate independently on the basis of clearly defined inputs, processes and outputs.

The PPM is defined as the process module primarily responsible for carrying out the desired transformation as part of a manufacturing step in accordance with DIN 8580. The energetic characterization of the PPM is based on Kreitlein [20] by BOPs. In turn, SPMs describe modules that are technically necessary for the transformation as part of the manufacturing step or required as additional steps due to set specific process conditions, for example peripheral process steps and machine components such as control systems. They therefore include all sub-processes that are not assigned to the direct manufacturing process in accordance with DIN 8580, but which contribute to the overall energy requirement. Hence, the side operation (SOP) is introduced which corresponds to the energetic description of an execution in a SPM. The energetic description can either be based on physical relationships, similar to the BOPs or on suitable approximation. Additionally, the models also account for loss operations (LOP) associated with the operating resources, which represent energy losses that do not contribute to the value-adding processes but are nonetheless part of the overall energy demand of the system. By combining the various BOPs, SOPs and LOPs into an EDM, the energy demand of a transformation can be determined.

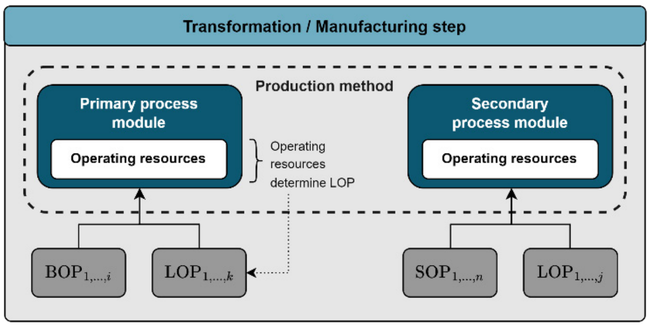

Figure 1: Schematic structure of the EDM

2.2. Definition of technical energy demand

The TED of a manufacturing step E_{tech} describes the total energy required to carry out a transformation based on PPMs and SPMs, considering the production method and the operating resources.

$$E_{tech} = \sum_i E_{PPM,i} + \sum_j E_{SPM,j} \tag{1}$$

The BOP-specific minimum energy demand E_{min} corresponds to the minimum amount of the total energy demand that must be used for the transformation and is equivalent to the physical EEB.

$$E_{min} = \sum_i E_{BOP,i} \tag{2}$$

The assisting energy requirement E_{ass} covers the minimum energy consumption of all components that are additionally required to technically carry out the manufacturing step and are expressed by secondary operations.

$$E_{ass} = \sum_i E_{SOP,i} \tag{3}$$

The energy loss requirement E_{loss} refers to all non-value-adding energy expenditure caused by energy-inefficient components and loss mechanisms. This share offers the potential for increasing EE. Apart from a complete change in technology, this is the amount of energy that can be saved by implementing EEM. E_{loss} is calculated from the sum of all energy requirements associated with LOPs.

$$E_{loss} = \sum_i E_{LOP,i} \tag{4}$$

Based on the operations, the total TED E_{tech} and minimum TED $E_{tech,min}$ shown in Figure 2 can be characterized as follows :

$$E_{tech} = \sum_i E_{BOP,i} + \sum_j E_{SOP,j} + \sum_k E_{LOP,k} \tag{5}$$

$$E_{tech,min} = \sum_i E_{BOP,i} + \sum_j E_{SOP,j} \tag{6}$$

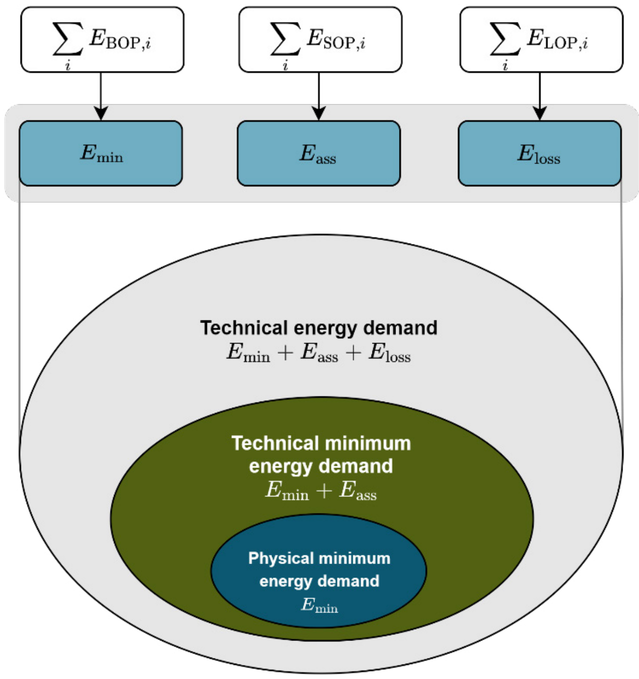

Figure 2: Calculation of technical energy demand and its components

2.3. Modular modeling of manufacturing processes and systems

For a holistic modeling of the TED of a manufacturing process all the manufacturing steps involved must be considered. The approach presented allows specific manufacturing steps to be modeled generically. Generic EDMs can be used for specific production scenarios. More precisely, EDMs are created for individual manufacturing steps. A modular aggregation of different manufacturing step-specific EDMs into a manufacturing process becomes possible as well as a further aggregation of different process-specific EDMs to form a production system. The overall benefit is the generic application of the modeled process operations or process modules in the context of other machines and processes. This requires material- and process-dependent parameterization.

Depending on the application, there is the possibility of energetic interactions between different EDMs that influence the EE of the overall process or system. In general terms, the energy loss demand can be described as the sum of losses of each EDM. Assuming that the share of the energy loss demand p_i of EDM_i can be utilized within the process or system, the aggregated total loss energy demand $E_{loss,agg}$ can be calculated using formula (7).

$$E_{loss,agg} = \sum_i (1 - p_i) \cdot E_{loss,EDM_i} \tag{7}$$

As a result, the TED of the entire production process or system is determined as:

$$E_{tech,agg} = \sum_i E_{min,EDM_i} + E_{ass,EDM_i} + (1 - p_i) \cdot E_{loss,EDM_i} \tag{8}$$

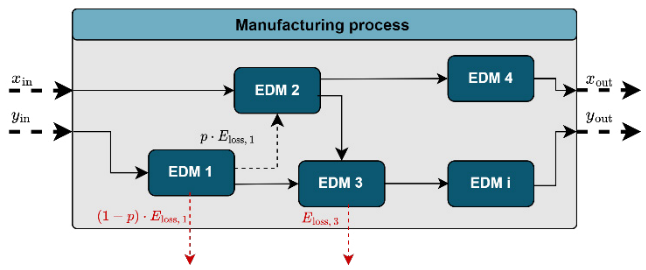

Figure 3: Schematic illustration of a sample manufacturing process with energetic interactions between EDM

3. Energy demand model development for case studies

3.1. Case studies

Vacuum annealing furnace (VAF): Steel is thermally treated using a time-dependent temperature and pressure curve with a maximum temperature of 1050°C and a low internal furnace pressure of 9 mbar in an annealing chamber. The vacuum generation is realized by using a diffusion vacuum pump for the initial vacuum generation and an additional vacuum holding pump. There is also a central cooling system for process and machine cooling.

Housing creation plant (HCP): In a production line, individual components of a housing are assembled using various sequential production steps. The focus here is on the steps of pre-tensioning and clinching. Local plastic deformations are generated to press the parts to be joined together by cold forming. Further process steps are neglected.

3.2. Vacuum annealing furnace

The single EDM of the VAF is divided into three process modules (see Figure 4). The annealing process is a PPM whose minimum energy demand $E_{min,A}$ is calculated using the BOP of 'thermal activation' expressed as $\dot{Q}_{th}$ [20].

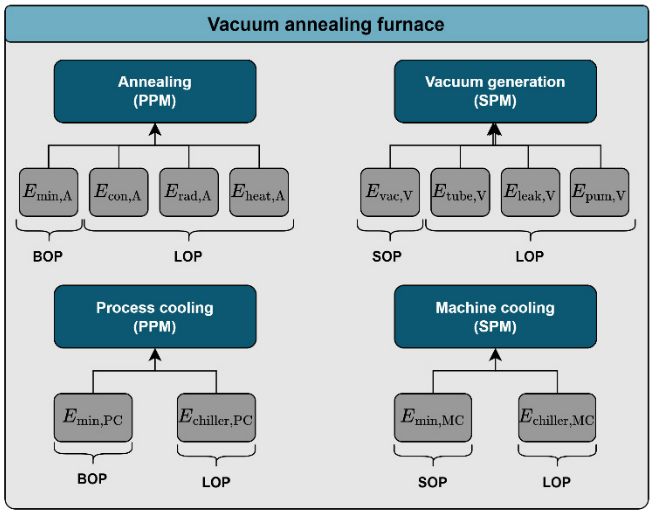

Figure 4: Structure of the EDM for the VAF

$$E_{min,A} = \int \dot{Q}_{th}(t)\, \partial t = \int \dot{m} \cdot c_p(T(t)) \cdot \Delta T(t) \partial t \tag{9}$$

The $E_{loss,A}$ is modeled based on LOPs of convective heat $E_{con,A}$, thermal radiation $E_{rad,A}$ and efficiency of the heating elements η_{heat} expressed as $E_{heat,A}$. The heating power also depends on the machine cooling power $\dot{Q}_{c,MC}$ during annealing.

$$E_{con,A} = \int \dot{Q}_{con}(t)\, \partial t = \int U \cdot A_{VAF} \cdot \Delta T\, \partial t \tag{10}$$

$$E_{rad,A} = \int \dot{Q}_{rad}(t)\, \partial t = \int \epsilon \cdot \sigma \cdot A_{VAF} \cdot \left(T_0^4 - T_{sky}^4\right) \partial t \tag{11}$$

$$E_{heat,A} = \int \left(\frac{1-\eta_{heat}}{\eta_{heat}}\right) \cdot \left(\dot{Q}_{con} + \dot{Q}_{rad} + \dot{Q}_{th} + \dot{Q}_{c,MC}\right) \partial t \tag{12}$$

The cooling processes of the furnace are considered in two process modules. The process cooling represents a PPM, while the machine cooling through gas quenching is defined as a SPM. In general, for the calculation of the cooling energy demand E_c the cooling power $\dot{Q}_c$ and the coefficient of performance (COP) is used. The minimum cooling demands $E_{\mathrm{min,PC}}$ for the PPM and $E_{\mathrm{min,MC}}$ for the SPM are determined by referencing to a Carnot process using the common formula (13). In turn, the energy losses $E_{\mathrm{cool,PC}}$ and $E_{\mathrm{cool,MC}}$ associated with the cooling system are specified based on the generic formula (14).

$$E_{min,C} = \frac{1}{COP_{Carnot}} \cdot \int \dot{m}_c \cdot c_p\big(T(t)\big) \cdot \Delta T(t)\,\partial t \tag{13}$$

$$E_{chiller,C} = \left(\frac{1}{COP} - \frac{1}{COP_{Carnot}}\right) \cdot \int \dot{Q}_c\,\partial t \tag{14}$$

The vacuum generation forms an SPM whose assistant energy requirement $E_{ass,V}$ is made up of the initial vacuum generation (SOP). The energy demand $E_{vac,V}$ is calculated by the effective suction power of the diffusion pump S_{eff} at intake socket of the furnace.

$$E_{vac,V} = \int S_{eff}(t)\,\partial t = \int p_{VAF}(t) \cdot V_{VAF}\,\partial t \tag{15}$$

The energy loss demand $E_{loss,V}$ is determined by the LOPs of the leakage losses S_{leak}, pipe losses S_{tube}, as well as the efficiency of the vacuum pump η_{pum}. The pressure difference between the pump and the intake socket nozzle is described by Δp. The atmospheric pressure p_0 is used to calculate the leakage

$$E_{tube,V} = \int S_{tube}(t)\,\partial t = \int \Delta p \cdot \frac{S_{eff}}{p_{VAC}}\,\partial t \tag{16}$$

$$E_{leak,V} = \int S_{leak}(t)\,\partial t = \int p_0 \cdot \dot{V}_{leak}\,\partial t \tag{17}$$

$$E_{pum,V} = \int \left(\frac{1}{\eta_{pum}} - 1\right) \cdot \left(S_{eff} + S_{tube} + S_{leak}\right)\partial t \tag{18}$$

3.3. Housing creation plant

The manufacturing process can be described by various EDMs whose TED can be summarized in a modular way for an assumed operating time t_{HCP} (see Figure 5).

The pre-tensioning manufacturing step is modeled by the PPM of tensioning and SPM of compressed air generation within *EDM₁*.

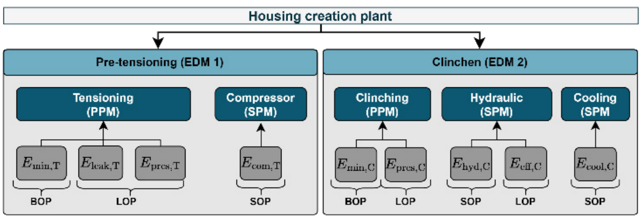

Figure 5: Structure of the EDMs for the manufacturing process of the HCP

$E_{min,T}$ refers as BOP to the minimum energy requirement required to close the compressed air rails. The energy required to move the piston in the pneumatic cylinder can be calculated by the force F on the piston and the moving distance s_{pneu} of the piston. The force is described by the pressure p_{pneu} applied to the pneumatic cylinder and its area A_{pneu}. The number of pneumatic cylinders n_{pneu} and the number of products manufactured n are needed to calculate $E_{min,T}$ for the period analyzed.

$$E_{min,T} = p_{pneu} \cdot A_{pneu} \cdot s_{pneu} \cdot n_{pneu} \cdot n \tag{19}$$

Leakage losses $E_{leak,T}$ and pressure losses $E_{pres,T}$ along the hoses from the central compressed air supply to the pneumatic cylinders result both as LOP. The pressure difference between the air compressor and the pneumatic cylinders is described as Δp_{pneu}. A distinction is made between the leakage flow $\dot{V}_L$ and the total volume flow $\dot{V}$.

$$E_{leak,T} = \dot{V}_L \cdot p_{pneu} \cdot t_{HCP} \tag{20}$$

$$E_{pres,T} = \dot{V} \cdot \Delta p_{pneu} \cdot t_{HCP} \tag{21}$$

The assistant energy demand of the central compressed air supply $E_{com,T}$ is calculated using an approximated specific power consumption for compressors $P_{com,T}$ as a function of the respective nominal pressure.

$$E_{com,T} = P_{com,T} \cdot t_{HCP} \tag{22}$$

The *EDM₂* for the clinching process is mapped via the PPM of clinching and the SPMs of hydraulics and cooling. As clinching itself is a joining process by forming in accordance with DIN 8580 it is considered by a PPM. The associated BOP-specific energy requirement results in $E_{min,C}$. The forming work required for this production process can be described by the BOP 'pressing' [21]. For simpler modeling, the energy demand is determined analogously to (19) on the basis of the change in position of the piston in the hydraulic cylinder in the clinching pliers. The number of clinch points per product is defined as n_{hyd}.

$$E_{min,C} = p_{hyd} \cdot A_{hyd} \cdot s_{hyd} \cdot n_{hyd} \cdot n \tag{23}$$

Similar to pre-tensioning, the LOP of pressure losses results in an energy loss requirement per clinching point $E_{pres,C}$. Leakage losses are neglected because leakage of hydraulic fluid during operation is excluded.

$$E_{pres,C} = \dot{V}_{hyd} \cdot \Delta p_{hyd} \cdot t_{HCP} \tag{24}$$

The average operating power consumption of the hydraulic system $\bar{P}_{hyd,C}$ was determined by measurement, so that the energy requirement is calculated according to formula (25).

$$E_{hyd,C} = \bar{P}_{hyd,C} \cdot t_{HCP} \tag{25}$$

The efficiency of the hydraulic system is indirectly quantified by the cooling capacity to be dissipated $\dot{Q}_{cool,C}$ and the total power consumption resulting in $E_{eff,C}$.

$$E_{eff,C} = \left(1 - \frac{\dot{Q}_{cool,C}}{\bar{P}_{hyd,C}}\right) \cdot \bar{P}_{hyd,C} \cdot t_{HCP} \tag{26}$$

The hydraulics are additionally cooled by a central cooling system (SPM) to dissipate waste heat generated by mechanical losses. Due to a lack of technical information, physical modeling is not performed. The assisting energy requirement results from the average electrical power demand $P_{cool,hyd}$ of the cooling machine. Due to a lack of technical information, LOPs are not analyzed.

$$E_{cool,C} = P_{cool,hyd} \cdot t_{HCP} = \frac{\dot{Q}_{cool,C}}{COP} \cdot t_{HCP} \quad (27)$$

3.4. Parameterization

The modeling of the VAF is based on a measured temperature and pressure curve during a representative batch. Regarding the modeling of the HCP, temporary measurements are partly used to determine the average operating performance of the system, e.g. the hydraulic total power and the dissipated cooling power. The detailed parameterization for both case studies was carried out using technical parameters from data sheets and the knowledge of the process experts.

4. Results and discussion

4.1. Analysis of technical energy demand

Vacuum annealing furnace: The TED of the VAF is calculated according to formula 5, where the summands are derived from formula 28 to 30.

$$E_{min,VAF} = E_{min,A} + E_{min,PC} \quad (28)$$

$$E_{ass,VAF} = E_{eff,V} + E_{min,MC} \quad (29)$$

$$E_{loss,VAF} = E_{loss,A} + E_{loss,V} + E_{chiller,MC} + E_{chiller,PC} \quad (30)$$

The calculated results shown in Table 1 give a total $E_{tech,VA}$ of 629,35 kWh. For a measured energy consumption $E_{meas,VA}$ of 661,4 kWh, this means a deviation of 4,85%. The share of energy loss in the TED is 61.8% and represents the maximum technical EEP.

Table 1. TED of the vacuum annealing furnace

Process module	E_{min}	E_{ass}	E_{loss}
Annealing	93,25 kWh	-	176,51 kWh
Process cooling	86,94 kWh	-	121,71 kWh
Machine cooling	-	60,19 kWh	84,26 kWh
Vacuum generation	-	46,36 Wh	6,45 kWh
Total	180,19 kWh	60,23 kWh	388,93 kWh

Figure 6 illustrates the measured and modeled load profile of the furnace and the temperature curve. The modeled power P_{VAF} is significantly higher than $P_{VAF,measured}$ at the beginning and at end because the cooling capacity is assumed to have a constant mass flow rate. In reality, power consumption can be assumed to be significantly lower at the beginning and end of the process. Due to a lack of technical details regarding the fans and pumps used in the cooling processes, the modeling does not include these.

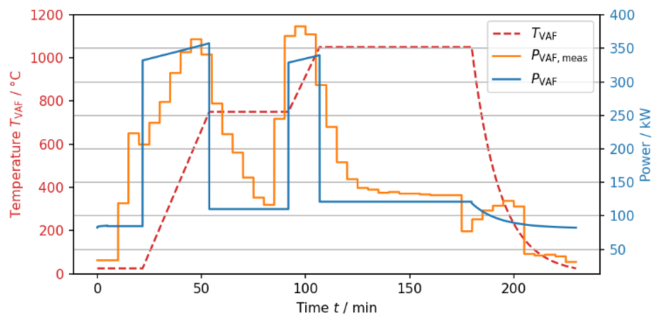

Figure 6: Validation of the modeled TED of the vacuum annealing furnace

Housing creation plant: By aggregating the energy requirements of both EDMs, the TED of the HCP is calculated based on formula 5 as follows:

$$E_{min,HCP} = E_{min,T} + E_{min,C} \quad (31)$$

$$E_{ass,HCP} = E_{com,T} + E_{hyd,C} + E_{cool,C} \quad (32)$$

$$E_{loss,HCP} = E_{pres,T} + E_{leak,T} + E_{pres,C} + E_{eff,C} \quad (33)$$

To determine the energy requirements, the operating process time $t_{HCP} = 300\text{s}$ is assumed, resulting in a total TED of 797,44 Wh for the process steps of pre-tensioning and clinching. It is assumed that 5 housings ($n = 5$) are produced. Table 2 shows the analysis for each process module. The validation of the modeling results with a measured load profile of the HCP shows a deviation of 4%. The maximum technical EEP is 35,86%. The energy losses of the central compressed air and cooling systems were not analyzed.

Table 2. TED of the housing creation plant

EDM	Process module	E_{min}	E_{ass}	E_{loss}
Pre-tensioning	Tensioning	0,12 Wh	-	6,80 Wh
	Compressor	-	44,38 Wh	-
Clinching	Clinching	3,65 Wh	-	0,02 Wh
	Hydraulic	-	369,98 Wh	279,15 Wh
	Cooling	-	93,33 Wh	-
Total		3,77 Wh	507,69 Wh	285,97 Wh

4.2. Limitations of the results

Generic modeling of the manufacturing processes is possible through the standardized structure of the EDM. However, an even more generic and automated approach requires a linking of the specific processes of DIN 8580 or the basic operations with representative SOPs and LOPs. Thus, transparency about the energy mechanisms and the specific process and machine parameters are still necessary to define the process modules and operations. Accurate physical modeling is particularly possible if a large proportion of the TED can be attributed to a small number of process modules that can be described independently of each other. For processes involving a large number of different components that are difficult to model without measured data, the approach reaches certain limits. Furthermore, the consideration of energy interactions and the use of energy losses between EDMs is only conceptually introduced, so that the applicability of the approach has yet to be proven.

4.3. Future research

Future research aims to determine process-specific EE benchmarks based on EnPIs to be developed as there is a need to determine the technical feasible EEP for a specific manufacturing process [3]. To this end, EE measures must be systematically derived to minimize the energy losses. When deriving EE measures, interactions between modular EDMs must be considered. However, future work should extend the scope of the EDM to map interactions at different levels from individual processes to the operational energy supply [23]. In addition, methods for integrating machine learning into physical modeling frameworks should be investigated to enable automated parameter estimation and enhance the robustness and applicability of this approach [3].

5. Conclusion

In this study a methodology for the development of generic EDM as the basis for EE analysis of manufacturing processes is presented. The EDM is structured into distinct process modules, each representing specific energy-related processes within a manufacturing step. This modular approach allows individual process modules to function as standalone EDM components, which can be flexibly combined to construct the overall EDM of a process. As a result, the EDM can be easily expanded with additional process modules, significantly enhancing the flexibility of the model for machine-independent applications. The method was tested in two case studies. For the case studies, it was shown that the approach can physically describe the TED with a validated accuracy of 95,15% and 104%. In addition, the method developed allows to quantify energy loss demands. By defining LOPs, the systematic and holistic identification of EEP and subsequent derivation of EE measures become possible through further research.

Acknowledgements

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