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September 3, 2026

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Doris Bernroider[1 [0009−0007−7089−8708]], Fabian Spitzer[1 [0009−0007−7827−6866]], Jochen Giedenbacher[1], and Holger Groening[1,2 [0000−0001−8241−591X]]

[1] University of Applied Sciences Upper Austria, Roseggerstraße 15, 4600 Wels, Austria

[2] Center of Excellence for Smart Production, Roseggerstraße 15, 4600 Wels, Austria

Preprint. Accepted for publication in the proceedings of EUROCAST 2026. This manuscript is the authors' version and may differ from the final published version.

Abstract. In this work, a hybrid modelling approach combining physical relationships with empirical data is proposed to estimate the electrical energy consumption of machining processes. Measurements indicate that only 5–10 % of the total energy consumed by the machine during the processing of the designed reference part is used for material removal. This share is estimated using the cutting force model proposed by Kienzle. The overall model, consisting of a machine model and a process model, is validated using data from an energy measurement system and a force measurement system. Validation is carried out for three different grades of steels (mild steel and tool steels), using material-dependent cutting parameters as well as dry machining and emulsion-based cooling. The results show that the proposed model achieves a deviation of less than 10 % compared to the measured energy demand. These findings demonstrate the potential of the approach as a basis for further refinements, such as incorporating tool wear, additional cooling strategies and non-electrical consumers. In addition, the proposed approach enables the integration of energy consumption into production planning and process optimisation, while maintaining a high degree of transferability to different machines, materials and process conditions.

Keywords: Energy Modelling · Energy Efficiency · Machining Processes.

1 Introduction

Machining processes represent a key technology in manufacturing and are associated with a significant share of industrial energy consumption. Increasing demand for sustainable production and improved energy efficiency requires a deeper understanding of the energy flows. However, predicting the energy demand of machining operations remains challenging due to complex interactions of process parameters, material properties and machine characteristics. This work proposes a physics-based modelling approach for estimating energy consumption of machining processes. Based on Kienzle's model [7] for cutting force determination, the approach combines a simplified model to represent machine behaviour. The objective is to provide an easy-to-use and transferable modelling framework, to enable energy estimation of machining processes and to improve the understanding of energy flows in machining operations. Following the state of the art, the energy estimation approach, model validation and results are presented. The paper concludes with a discussion section, and an outlook for future research (Fig. 1).

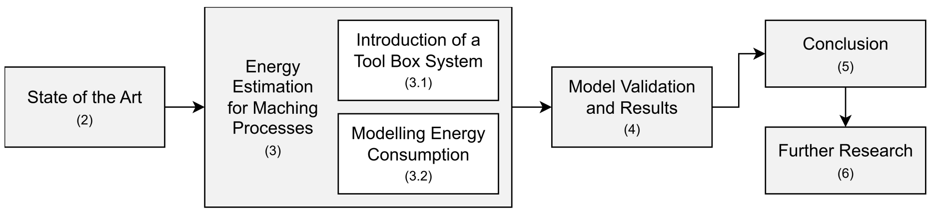

Fig. 1. Structure of the Paper

2 State of the Art

The manufacturing sector is a vital part of modern industrialised societies and plays a decisive role in economic growth and prosperity. At the same time, the manufacturing industry is responsible for a substantial share of global energy consumption. Estimates from international energy agencies and scientific studies indicate that industry accounts for 25 to 40 % of global final energy consumption, with a significant proportion attributable to manufacturing processes. Since the year 2000, global industrial energy demand has increased by around 70 %, corresponding to an average annual growth of approximately 1.3 % between 2010 and 2022 [6]. Consequently, the manufacturing sector bears a major responsibility in achieving the transition towards energy-neutral production. Machine tools represent a core component of industrial manufacturing and constitute a significant part of energy consumption due to their high power consumption and diverse operating conditions. In 2018, the industrial sector accounted for approximately 38 % of global electricity demand [6]. An analysis of the German machine tool market further indicates that approximately 70 to 80 % of installed machines are metal-cutting machine tools [4]. As a result, cutting machine tools alone are estimated to be responsible for up to 700 TWh globally, with an upward trend. Moreover, machine tools are often characterized by considerable energy losses. For these reasons, machine tools represent a promising and effective starting point for energy efficiency measures in the manufacturing industry [4]. In order to utilise knowledge about the energy consumption of cutting machine tools in simulations and optimisation studies without relying on time-consuming measurements, energy modelling approaches are commonly used. In the field of energetic machine models, the literature focuses primarily on the detailed representation of specific machines and processes. Leherbauer, Zhao and Li show examples of the development and implementation of detailed physical machine models [8, 9, 11]. These approaches typically require a large number of input variables, as well as a comprehensive and precise understanding of the machine, its subcomponents, and their interactions during defined processes. Zhao investigated the influence of tool wear and machining parameters and concluded that the energy demand of a machine tool is proportional to the volume removed by machining and exhibits a linear relationship with tool flank wear and the spindle speed. Furthermore, it was shown that the specific energy consumption of the machine decreases with increasing material removal rate [11]. Gontarz et al. propose a modular, physics-based approach, founded on a component- and state-based framework. Their model describes the internal energy flows of the machine and, in addition to the process description based on the Kienzle model, explicitly considers auxiliary equipment such as pumps, fans, and the compressed air supply. The modular structure of the model aims to enhance the comparability of different machine configurations. Experimental validation using a lathe demonstrated deviations of less than $\pm$ 20 %, compared to measured energy consumption values [5]. Another approach pursued in research consists of data-driven models. These methods are often expected provide higher predictive accuracy and robustness in estimating the energy consumption of machine tools. Bhinge et al. use a machine learning tool, the Gaussian Process Regression to predict the energy demand [2]. However, effects such as tool wear are not considered in the approach, nor is the transferability of the trained model to other machines. Brillinger and Nugrahanto compare different machine learning methods for predicting energy demand and for identifying energy-efficient strategies in milling operations [3, 10]. These models provide accurate, data-driven forecasts, but highlight the high data demand and limited transferability to other machines.

3 Energy Estimation for Machining Processes

3.1 Introduction of the Tool Box System for Modelling Energy Demand

The state of research demonstrates that existing models achieve a high level of accuracy but are typically highly specific and therefore limited in their ability to generalise on similar problems. To describe knowledge on the energy consumption of machines and the manufacturing of different components in a simplified and application-oriented manner, models are required that can predict the energy demand in production and thereby enable the identification of optimisation potentials. For this purpose, knowledge-based modelling approaches are combined with empirical data. Such models are essential for understanding energy flows within manufacturing processes. Optimisation spans multiple levels: product design, the selection of manufacturing strategies, the choice of material and machining parameters, and the production scheduling. Addressing these optimisation tasks requires models that are applicable to different machines, tools and production systems, that cover a variety of processes and strategies, and that are capable of representing different components to be manufactured. As introduced in [1], the contribution to this work lies in the development of a modelling approach that is intuitive and transparent, with a particular emphasis on machining processes. The model is based on fundamental physical relationships and established equations, such as the cutting force model according to Kienzle. To systematically assess the identified optimisation potentials and derive practical strategies to reduce the overall energy demand, a structured representation of energy consumption is required. For this purpose, two complementary perspectives are combined, enabling a clear and systematic description of both the machine and its subsystems, as well as the manufacturing process itself. The objective is to estimate the energy requirement for the production of a defined component on a defined machine for the first time using a modular modelling framework.

Component level:

ISO 14955-1 provides a standardised framework for classifying energy consumers to ensure the comparability of measurements. In accordance with this standard, the individual energy consumers of a machine are grouped into energy-relevant functional categories: *Motion Systems, Media Supply, Support and Conveyor System, Temperature and Pressure Control, Control and Automation Technology and Safety.* Taking a milling centre as an example, the machine axes and the spindle are assigned to the *Motion System* category, the hydraulic system and the coolant supply to *Media Supply* and the chip conveyor to the *Support and Conveyor System* category. Depending on the current operating state of the machine, the energy demand of the individual consumers and thus of the respective consumer groups varies. In this aggregated form, the consumption behaviour can be generalised and interpreted in a clear and structured way. For each individual consumer, the relevant power quantities and the usage factors are determined, enabling a quantitative description of energy consumption at this level of detail.

Process level:

Machining processes are represented based on cutting forces. For this purpose, the cutting force model according to Kienzle is applied, which describes cutting and chip formation forces as a function of the material, tool, machining parameters, and the specific operation. The cutting force is expressed as $F_c = k_{c1,1} \cdot b \cdot h^{1-m} = k_c \cdot A$ where $k_{c1,1}$ denotes the specific cutting force for a reference chip cross-section with a chip width of $b = 1\ mm$ and chip thickness $h = 1\ mm$. The parameter m is a material-dependent exponent, describing the nonlinear dependency of the specific cutting force k_c on the uncut chip thickness h. The specific cutting force implicitly includes further influences such as tool geometry, cutting conditions, and process-related effects, as these are reflected in empirically determined parameters. The chip cross-section A is defined as $A = b \cdot h$. Using the physical relationship $P = F \cdot v$, the calculated forces can be converted into mechanical power and, by applying efficiency coefficients, into electrical power. In this way, the energy demand of the machining process can be estimated using a model-based approach.

These two perspectives are represented by two types of toolboxes. On the one hand, the *Machine Tool Box* enables the energy modelling and parametrisation of different production machines by appropriately combining the individual components of the system. On the other hand, the *Process Tool Box* is used to represent and parametrise the energy consumption of machining operations to be performed. The combination of a machine configuration derived from the Machine Tool Box and a process configured with the Process Tool Box provides an initial estimate of the energy demand associated with manufacturing the specified component and performing the defined processing steps on the selected machine.

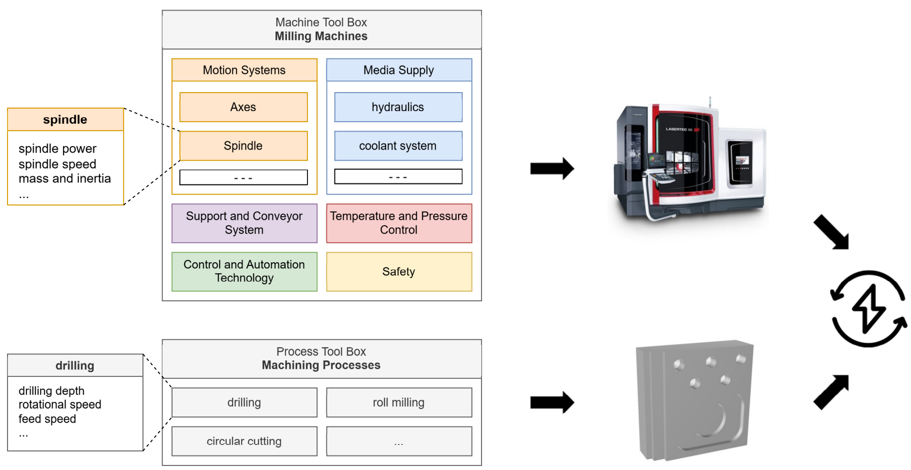

Fig. 2. Energy estimation by modelling machines and processes by using machine tool boxes and process tool boxes.

In order to support structured modelling in the initial phase, a reference part was designed to feature a broad range of machining strategies and production operations, as well as enable machining on conventional 3-axis milling centres. The resulting reference part, shown in Figure 3, has overall dimensions of 100 mm x 100 mm x 20 mm and incorporates a variety of geometric features, including holes, rectangular and round pockets, milled shoulders, as well as an extension of phases, curves and threads. By including these different operations, it is intended to provide insights into their respective energy demands, support the implementation of different strategies, and enable the transfer of the obtained knowledge to the modelling of other part.

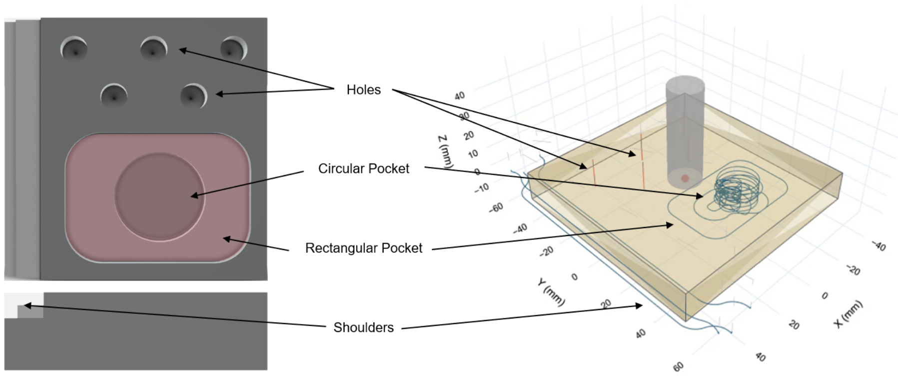

Fig. 3. 3D model of the reference part with different features and processing tool path.

During the machining of the reference part, two different measurement systems were used. To measure the total consumed electrical energy of the milling machine, current clamps were utilized. From the measured electrical current, power and energy consumption were derived. This measurement system also allows flexible energy measurement of individual consumers. Additional data is collected by interfacing with the machine controller, enabling the acquisition of parameters such as feed rates, rotational speeds, spindle speed, and motor temperatures. The overall structure of this system is illustrated in Figure 4.

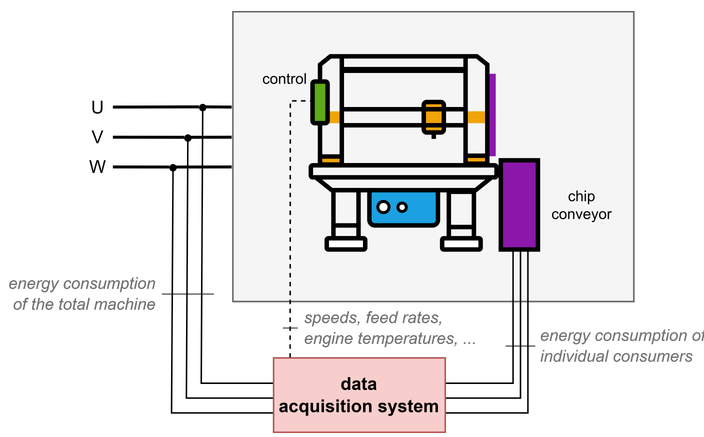

Fig. 4. Measurement system for measuring power and energy consumption of the total machine and for acquiring additional machine parameters.

As a supplementary measuring system, a force measurement platform was implemented to determine the forces occurring on the workpiece during machining.

As shown in Figure 5, the component to be machined is mounted directly on the force measurement system. The setup enables the measurement of the forces in the x, y and z directions as well as the torque around the z-axis. Based on these measurements, the resulting cutting force can be calculated. Its direction depends on the machining strategy and the specific machining operation, while its magnitude is defined by the chosen machining parameters. These two measurement systems enable the validation of the developed model and contribute additional empirical insights to the physics-based modelling approach.

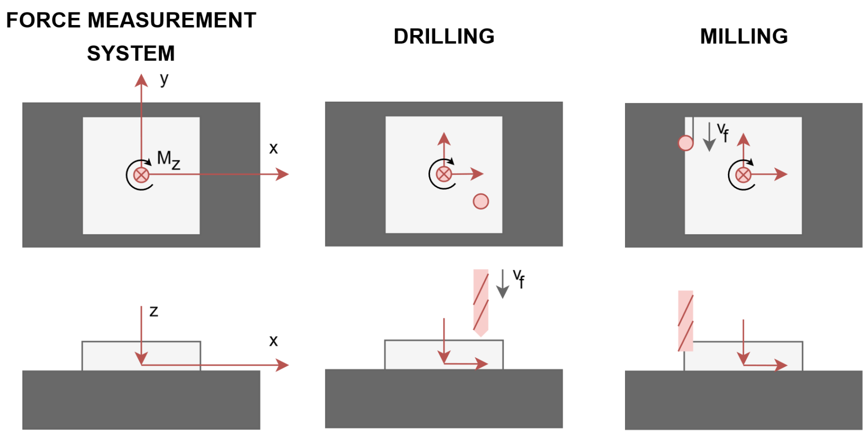

Fig. 5. Force measurement system to measure the forces occurring on the workpiece during machining.

3.2 Modelling of the Energy Consumption of a Milling Machine during Machining

A DMG MORI LASERTEC 65 3D machining centre was used for modelling and its components and electrical energy consumers were analysed. Based on the recommendation of ISO 14955-1, the individual consumers of the machine were classified into the categories *Motion Systems, Media Supply, Support and Conveyor Systems, Temperature and Pressure Control, Control and Automation Technology and Safety.*

The mathematical modelling of energy consumption is performed using the nominal power P_N specified in data sheets combined with a utilisation factor ξ. This utilisation factor considers the operating point of the consumer and losses for example mechanical friction or electrical inefficiencies. The product of the nominal power and the utilisation factor yields the active power P. The following Equation 1 shows the general calculation of the active power of a defined consumer i from a set $\mathcal{C}$.

$$P_i = P_{iN} \cdot \xi_i, \quad \text{with } i \in \mathcal{C} \tag{1}$$

The instantaneous power consumption of all active energy consumers P_{total} is summed at a given point in time (Eq. 2). Integrating this time-dependent power over the corresponding time interval t leads to the total energy consumption E, as shown in Equation 3.

$$P_{total} = \sum_{i=1}^{n} P_i = \sum_{i=1}^{n} (P_{iN} \cdot \xi_i) \tag{2}$$

$$E = \int P \, dt \tag{3}$$

These equations are applied to model the baseline energy demand of the different cooling systems and machine axes.

For the mathematical modelling of the spindles energy consumption, the no-load consumption $P_{S_{IDLE}}$ is added to the cutting performance $P_{S_{WORK}}$ and supplemented by an additional factor P_{ξ_i} accounting for mechanical friction losses, electrical inefficiencies, and transient states. The spindle power demand depends on the speed as well as the required cutting force, which varies with the machining operation and therefore changes over time.

$$P_S\,(n,t) = P_{S_{IDLE}}\,(n,t) + P_{S_{WORK}}(n,t) + (P_\xi) \tag{4}$$

The spindle no-load curve of the machine was determined through a series of measurements. The cutting power is derived from the cutting force, which can be obtained using the integrated force measurement system. As an alternative to direct force measurement, the cutting force can also be estimated using the Kienzle cutting force model described in Equation 5.

$$F_c = k_{c1,1} \cdot b \cdot h^{1-m} = k_c \cdot A \tag{5}$$

The variables and parameters of the model are defined in the previous section 3.1. Thus, the cutting force can be determined based on the selected machining parameters and used to calculate the cutting power. The results of the energy modelling of the structural steel reference part on the selected machine yield a model of power and energy consumption, as shown in Figure 6. The timing intervals of the model are taken directly from real measurement data recorded during the machining of the St37 reference part.

Further experimental series were carried out to validate the developed model. The reference part was machined from three different grades of steel: St37/S235JR (mild steel), 1.7225/42CrMo4 (tool steel) and 1.2842/90MnCrV8 (tool steel). The processing parameters were adapted to each respective material. The machining operations were performed using a twist drill with a diameter of 10.2 mm and a four-flute end mill with a diameter of 16 mm. The experiments were carried out both under dry machining conditions and with coolant emulsion. For validation purposes, an additional measurement under zero load was conducted in each case to determine the energy demand associated with machine operation, excluding energy used for chip deformation and removal. The modelling of

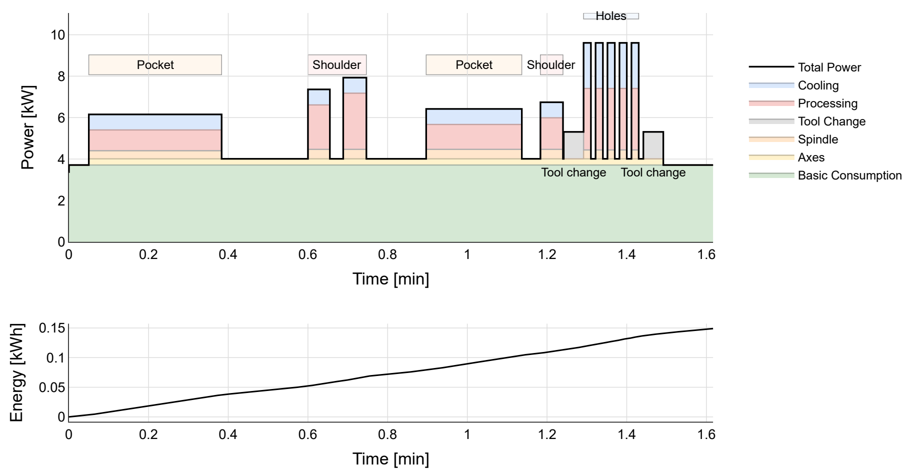

Fig. 6. Exemplary results for energy estimation processing the reference part on the selected machine.

these experiments was again carried out by calculating the cutting forces and incorporating the additional energy demand resulting from the use of cooling lubrication, as illustrated in Figure 8. It should be noted that material-specific machining parameters are used for each material. As a result, the measured cutting forces and machining times differ between the materials, which leads to variations in the machine's cumulative energy demand.

4 Model Validation and Results

The following section is dedicated to the validation of the proposed model using three different materials and dry milling and emulsion for cooling. Based on the defined cases (Table 1), different evaluation results and findings are presented. Furthermore, energy data, collected by the introduced measurement system, is compared with force measurement data and calculated forces and energy.

Table 1. Cases used for model validation.

Case	Material	Cooling Strategy
1	St37 / S235JR (mild steel)	dry milling
2	St37 / S235JR (mild steel)	emulsion
3	1.2842 / 90MnCrV8 (tool steel)	dry milling
4	1.2842 / 90MnCrV8 (tool steel)	emulsion
5	1.7225 / 42CrMo4 (tool steel)	dry milling
6	1.7225 / 42CrMo4 (tool steel)	emulsion

Five repetitions of drilling identical holes are used to evaluate the repeatability and stability of the process. The analysis of the feed force F_f for St37 steel shows a coefficient of variation of < 2 %, increasing to < 4 % when all three steel materials are considered. Similarly, the cutting torque M_z exhibits a coefficient of variation of < 4 % for 1.7225 tool steel and < 10 % across all of the selected materials. The higher variation in the measured cutting torques compared to the feed forces can be attributed to small geometrical deviations of the dill sleeves, which generate minor circumferential forces. Due to the distance between the hole and the centre of the force measurement platform, these forces induce additional torques that affect the measurement. As a result, the measured torque values show increased variation. However, this effect is related to the measurement setup and does not indicate an instability of the cutting process. Therefore, the milling process can be considered stable. This conclusion is further supported by the coefficient of variation of the measured power, which remains below 6 %.

Comparing the mean cutting force resulting from the force measurement with the calculated cutting force according to equation 5, the difference in the constant force is approximately 2.5 %, excluding outliers. By including the transient part of the force when the drill enters into the material, the discrepancy between calculated and measured cutting force for all used materials is around 3.3 %. As indicated, the basic material property parameters from literature are used in the calculation, which do not perfectly fit the real material. Furthermore, tool wear has been neglected completely. Nevertheless, the calculation of cutting forces and torques is a valid method with sufficient predicting accuracy.

The accuracy, comparing the calculated cutting power and the measured cutting power, reaches a mean value of 5.1 % with a maximum of 11.8 % considering the forces in the constant range. Comparing the calculated power values with the measured power values exhibit an average accuracy of 7.4 %. Therefore, the unknown deviation of the force measuring system and the energy measurement must be taken into account.

To generalise the modelling of energy for material removal, the relationship with the specific cutting force is considered. Using the specific cutting force k_c, resulting from the model of Kienzle and defined as $k_c = \frac{F_c}{A}$, together with $P_c = F_c \cdot v_c$ and $Q = A \cdot v_c$, the relation $k_c = \frac{P_c}{Q}$ can be derived. Based on the volume of material removed per time unit Q, the energy demand for chip deformation and removal is estimated using Equation 6.

$$P_c = k_c \cdot Q \;\rightarrow\; E = k_c \cdot V \tag{6}$$

The following Table 2 shows the deviation between measured and calculated values, as defined as follows:

$$\text{deviation [\%]} = \frac{\text{measured value} - \text{calculated value}}{\text{measured value}} \tag{7}$$

With the rising abstraction of the processes of material removal, the accuracy in every step from force values to energy values is decreasing due to uncertainty introduced by the manual data analysis and measurements. Generalisation through the specific cutting force according to Kienzle and extracted from the measured energy value and the volume (Eq. 6) achieved a minor deviation of 2.7 %, resulting in a highly suitable method for energy consumption estimation.

Table 2. Achieved deviations compared measurements and calculations.

Compared Values	Average Deviation [%]
measured cutting torque vs. calculated cutting torque	2.4
measured cutting power vs. calculated cutting power	5.1
measured cutting energy vs. calculated cutting energy	7.4
kc (energy measurements) vs. kc (force calculation)	2.7

The following illustration (Fig. 7 left) shows the share of electrical energy used for removing material, referred to the total energy consumption of the machine. The graphic on the right side shows the share for removing the material only during the drilling process itself. Depending on the machining parameters and the active cooling strategy (emulsion or dry machining), only around 4 to 38 % of the energy during the short time of drilling the hole is used for chip deformation and removal. The remaining energy is consumed by auxiliary units, such as the control system, axis drives, or coolant pumps. Considering the described use cases, only around 5 to 10 % of the total energy during the full process is used for material removal. The total energy consumption is higher when using emulsion for cooling. This is due to the additional electrical consumers for coolant supply and coolant preparation that are active in these cases. Additionally, comparing

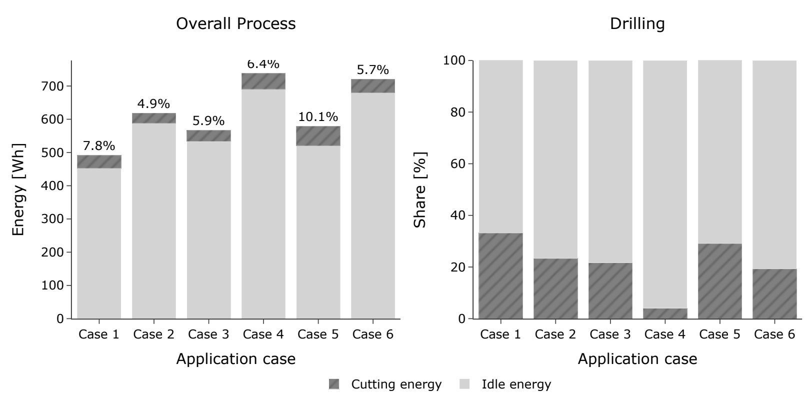

Fig. 7. Shares of energy used for removing material and auxiliary units.

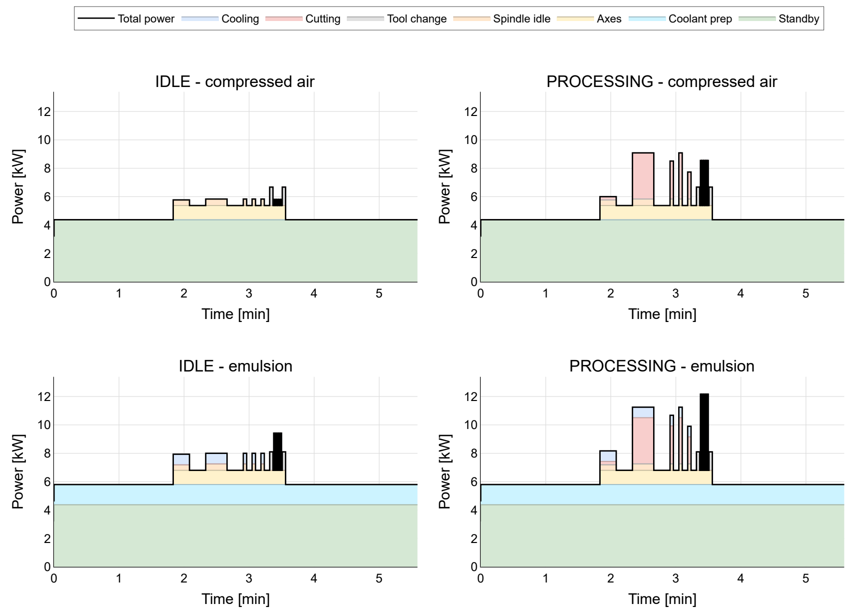

Fig. 8. Energy estimation of the defined milling machine for processing the defined reference part from mild steel comparing emulsion for cooling and dry machining.

the calculated energy amount for the cutting process with material specific data from literature, small deviations from measured values are shown. One reason, therefore, is the material specific values $k_{c1,1}$ and m for calculating the cutting force. These guide values presented in literature do not perfectly fit the conditions of the real material. Furthermore, the basis model of Kienzle does not consider cooling strategies. The performed measurements show that, depending on the cooling strategy (dry machining or emulsion), the cutting energy differs by about 30 %. This indicates that considering the cooling strategy in calculations is necessary for achieving a higher estimation accuracy in modelling.

Figure 8 presents the final model for estimating the energy demand associated with processing the defined mild steel reference part. A comparison between dry machining and machining with emulsion cooling is provided. The contributions of the individual energy consumers are visualized, and the idle condition (without material removal) is included on the left-hand side. Using the proposed machine model with simplified and optimized parameters, together with the cutting energy estimated based on the Kienzle approach, a deviation of less than 7 % between the estimated and the measured energy demand was achieved.

In Figure 9, a Sankey diagram is presented to illustrate the distribution of energy among different consumer categories at a specific time point t. In this representation, only the energy used for cutting is classified as value-adding energy share, whereas the remaining energy is classified as non-value-adding.

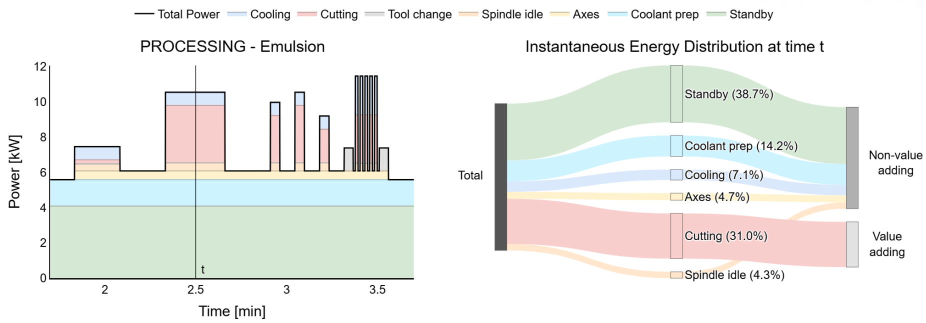

Fig. 9. Illustration of instantaneous energy distribution at time t using a Sankey diagram to support a better understanding of the systems energy flows.

5 Conclusion

This work demonstrates a physics-based approach for electrical energy modelling of machine tools and machining processes. Using the proposed toolbox system, the approach aims to achieve transferability to different machines using the knowledge of basic parameters like power and energy consumption, as well as already known relationships described by Kienzle. The objective is to formulate easily transferable, universal relationships of different disciplines for modelling machines and processes, supporting users and operators by enhancing their understanding about energy flows and the required amount of energy necessary for manufacturing components and operating machine tools. Taking a milling machine as an example, the proposed approach was used for estimating a machine's energy consumption for manufacturing a designed reference part. This part was manufactured from three different grades of steel (mild steel and tool steels) with defined, material specific parameters using identical tools. The proposed model was validated using this reference part and the defined milling machine. Observing a drilling process shows that between 4 and 37 % of the energy was used for material removal, depending on the material and the cooling strategy. Analysing the whole manufacturing process displays that, only 5 to 10 % of the total energy was used for chip deformation and removal. The remaining share is used for axis drives, control systems and auxiliary units used for coolant supply and treatment. Validating the model using energy and force measurement data shows a minor deviation of 2.7 % referring to the specific cutting force according to Kienzle. By using a machine model, based on this approach, with simple, optimised parameters, a deviation between the estimated and the measured energy consumption of less than 10 % (with deviations below 7 % for the investigated case) was achieved. Measurement data indicates a difference between the cutting energy using emulsion for cooling compared to dry machining of on average 30 %. This is not considered in the basic cutting force calculation by Kienzle. Summarising, with this model, based on simple physical relationships and complemented with empirical data, an initial estimation for the amount of energy used for machines and for production processes is possible with sufficient accuracy. The model also provides insights into the systems energy flows and it can be used as an input for energy reduction in production systems and processes.

6 Further Research

The presented model is used as a basis for enabling further developments and extensions discussed subsequently, emphasising on expanded validation approaches to examine transferability to other machines, materials and processes. The toolbox system aims to achieve transferability. This means the approach should not only be used for one milling machine as evaluated in this paper; it should be used to model the energy consumption of different milling machines. In addition, this modular and parametrisable approach is not limited to milling machines or machine tools. Further evaluations for demonstrating how and to what extent this modelling technique can be used in further production technologies like forming technology and additive manufacturing, must be conducted. In this work, model validation was limited to one milling machine, a defined part and three grades of steel. Although the designed part exhibits different features such as holes and pockets, expanding evaluation to different milling strategies like free form milling can provide additional insights. Furthermore, the limitation of only three materials (mild steel and tool steels), processed using material specific cutting parameters, restricts the scope of the model application and requires an extension of the experimental setup to materials like high-tensile steel, titanium, or non-ferrous metals as well as variations in process parameters. Further, the use of different milling machines contributes to a significant quality increase when evaluating the transferability of the model. At the current state of research, the model is restricted to electrical consumers. As becomes clear in this case, a mathematical description of the amount of coolant lubrication and the consideration of compressed air preparation are not included. An extension of the model is necessary for evaluating different cooling and lubrication strategies. As the results show, the cutting energy using dry machining differs from using emulsion in average about 30 %. The impact of cooling and lubrication strategies is not considered in the basic model of Kienzle. An extended model may potentially increase estimation accuracy by including a mathematical formulation of the impact of cooling and lubrication strategies in the model. Another point for improvement can be found in the optimisation of the specific cutting force by adjusting the values found in literature to actual material properties. In the proposed model, the cutting force was calculated manually using static values for the depth of cut. As a result, the estimated processing time is underestimated, since the tool entry phase is not considered. By using the NC code for calculating the cutting forces based on a time-dependent (dynamic) depth of cut, the estimation of both processing time and energy consumption may be improved.

Concluding, the application area of this modelling approach offers great potential for further studies. These include the consideration of how and where these models can be applied, using this knowledge for energetic modelling in production planning and process optimisation.

Acknowledgments. This work was supported by the research project ENPro. The project ENPro is financed by research subsidies granted by the government of Upper Austria.

Disclosure of Interests. The authors have no competing interests to declare that are relevant to the content of this article.

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