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A Methodology for Customized Prediction of Energy Consumption in Manufacturing Industries

Christopher Schmidt[1,3,#], **Wen Li**[2,4], **Sebastian Thiede**[1,3], **Sami Kara**[2,4], and **Christoph Herrmann**[1,3]

1 Joint German-Australian Research Group, Sustainable Manufacturing and Life Cycle Engineering, Technische Universität Braunschweig, 38106 Braunschweig, Germany
2 Joint German-Australian Research Group, Sustainable Manufacturing and Life Cycle Engineering, The University of New South Wales, 2052 Sydney, Australia
3 Institute of Machine Tools and Production Technology (IWF), Technische Universität Braunschweig, Langer Kamp 19 b, 38106 Braunschweig, Germany
4 Sustainable Manufacturing and Life Cycle Engineering Research Group, School of Mechanical and Manufacturing Engineering, The University of New South Wales, 2052 Sydney, Australia
Corresponding Author / E-mail: christopher.schmidt@tu-bs.de, TEL: +49-531-391-7169, FAX: +49-531-391-5842

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Regulative measures and rising energy cost foster the trend towards energy efficient manufacturing. However, companies are facing hurdles such as high effort and little expertise when implementing energy efficiency measures. Moreover, the embodied energy of products cannot be determined accurately in eco-assessments of factories. This paper presents a methodology for the reliable prediction of energy consumption of arbitrary manufacturing processes. It is based on minimal measurements and requires little effort and previous knowledge due to precise guidelines. Consumption models help to allocate energy cost to products, to calculate the product carbon footprint and to derive and validate measures to improve energy efficiency in production. The methodology has been applied in a medium size company with a large number of different products and machines.

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NOMENCLATURE

a, b = coefficients
C_0, C_1 = machine-specific coefficients
E_{annual} = annual energy consumption of process
e_{heat} = energy demand per cm³ (induction heating)
e_i = specific energy consumption (i^{th} operation mode)
E_i = Energy amount (i^{th} operation mode)
E_{part} = energy consumption per product
$E_{per\ place}$ = Energy per place on conveyor
E_{stroke} = energy consumption per stroke
m = No. of different products going through a process
n_{heater} = No. of active nozzle-heater units
n_m = annual number of product m
$n_{per\ cycle}$ = parts per cycle
n_{stroke} = number of strokes
P_{avg} = averaged (constant) power level
$P_{coat,\ avg}$ = average power level of powder coating line
P_{idle} = idle power level
SEC = specific energy consumption
$t_{annual,run}$ = annual runtime of machine
$t_{annual,setup}$ = annual setup time of machine
t_{cycle} = cycle time of the product
t_{idle} = idle time per product
t_{stroke} = duration of stroke
V = volume of machined material
V_{part} = volume of part
x = key process parameter

1. Introduction

Energy costs have been rising over the last decades, and manufacturers start to consider energy as a valuable resource instead of overhead cost item. All forms of energy supply and usage cause emissions (e.g. carbon dioxide) which contribute to environmental problems.[1] Binding emission reduction targets, such as the Kyoto Protocol also add pressure to the manufacturing sector.[2] Additionally, a growing demand of consumers for eco-products can be observed.[3] Therefore, more and more companies take action to increase their energy efficiency in order to remain competitive.

Implementing a continuous improvement process, however, often faces limitations because resources like personnel, time and knowledge are lacking. Moreover, lack of transparency in relation to energy consumption and energy hot spots further hinders implementing improvement measures with an adequate leverage effect.[4] Energy consumption is driven by production machines, technical building equipment, as well as office areas etc. in the form of various energy carriers such as electricity, gas and diesel. This paper focuses on the electricity consumption in the production area. In order to identify improvement measures in the first place, it is essential to gain insight into the machine characteristics in terms of electrical energy consumption, which mainly relies on empirical measurements. Especially in a complex production system with multiple products (e.g. a job-shop production environment), it is infeasible to measure each manufacturing process for every product.

Therefore, this paper introduces an approach which overcomes the aforementioned barriers towards energy transparency and focuses on a practical application in industry. The methodology is based on a principle of minimal measurements. A decision tree is provided to derive the necessary extent of measurements. Based on the metering of producing one or two products, energy models can be derived to predict the required energy for making any given product with the same machine. The proposed methodology is validated with a real industrial case which also reveals the benefits of this approach.

2. Review on Energy Consumption Prediction of Machines

This section presents existing approaches in relation to energy consumption prediction of manufacturing processes. Reports of their application in industry are also reviewed. Accordingly, requirements for a successful implementation in industry are derived to further assess the applicability of existing approaches. An overview of published ranges of energy demands for various manufacturing processes is provided by Yoon et al..[5]

2.1 Estimation through Exergy Framework

Manufacturing processes transfer material inputs into products and wastes while converting energy inputs into useful work and waste energy such as heat.[6] This process can be generalized by the thermodynamic concept of exergy, which reflects the maximum useful work possible during a process. Gutowski et al. applied this concept for a wide range of manufacturing processes, and have revealed a reverse trend between specific energy consumption (SEC) and process rate.[7] A theoretical equation of depicting SEC is also proposed. However the coefficients are missing, hence the approach cannot be directly used to predict energy consumption for a specific machine tool. Renaldi et al. further investigated the application of exergy analysis application in discrete manufacturing processes and described various hurdles. Their focus is on the identification of inefficiency sources and a unified metric to describe the quality of both energy and material.[8]

2.2 Estimation through Nominal Power

Thiede et al. introduced a quick method for energy consumption estimation of machines which is easy to apply and addresses the needs of small and medium size companies. The estimation is based on the nominal power from type plates or machine specifications. These values are generally too high since they reflect the maximum operational power.[4] He et al. devised a method to estimate energy consumption of NC machining that uses the correlation between NC codes and energy consuming components. Based on specific NC tags (M, S, G, F, T), the machine components show a characteristic behavior that can be linked to their energy consumption. Similarly, power ratings of components are used for the estimation which resulted in overestimation of the total power consumption of a machine.[9]

2.3 Estimation through Simulation

The energy consumption of production machines can also be predicted by discrete event simulations (DES). The prediction is based on different operational states of the machine which are defined by certain components being either active or not. These states are further linked by transitions which show possible changes and temporal behaviors between states (e.g. spindle acceleration). The shares of each state over the total runtime can be determined empirically or through machine usage scenarios.[10,11] Frigerio et al. use a similar approach to model complex machines. In their approach, the machine is divided into functional modules. All of which are then modeled in terms of states and events with automata theory and their relationships are defined using a specific logic.[12] Another component-based approach was developed by Frigerio et al..[13]

Abele et al. introduced a simulation-based methodology for a generic description of production machines, which can be used for decision support in early stages of production planning as it allows the choice of most energy efficient processes. The machine is decomposed into a number of components whereas they are sorted into standard categories in this approach.[14] Such simulation models can also be connected with the hardware machine control system to utilize NC-code information in order to predict the energy demand for a specific production task.[15] However, developing such simulation models requires enormous efforts and special knowledge into the component level of machine tools. In addition, this methodology is restricted to CNC machines. Consequently, industrial applications in a large scale are rarely seen in publications or reports.

2.4 Estimation through Empirical Models

Kara and Li developed a methodology for a reliable prediction of unit energy consumption for material removal processes.[6,16] An empirical model is used to characterize the relationship between process parameters and energy demand. The specific energy consumption (Wh/cm³ of material removed) is modeled depending on the material removal rate (MRR) as the decisive parameter. Measured data is analyzed with SPSS software. Machine specific coefficients need to be determined. This model is then able to describe the specific energy consumption under various cutting conditions with an overall accuracy of over 90%. However, as the coefficients are machine specific, the methodology has to be repeated for each machine tool and process. The same empirical approach has been also applied to other processes, such as injection molding[17] and extrusion.[18]

2.5 Industrial Requirements and Published Applications

Literature about the state of practice of the presented approaches is summarized in this section. Only a few practices have been reported with a number of industrial requirements. This paper further extends the list of these requirements which are considered essential for a successful application in industry. Strengths and weaknesses of the existing methods are then assessed according to what extent they meet those requirements.

Renaldi et al. discussed the hurdles towards the application of exergy framework method in industry. Since the exergy framework was originally designed to assess thermal processes, other processes (e.g. turning, grinding, etc.) face difficulties to quantify the exergy during a proces.[8] As mentioned before, the exergy model is not suitable for application due to the lack of specific values for the model coeffcients.

On the contrary, the nominal power approach is proven to be highly practical. However, results are lacking the necessary accuracy, therefore inadequate for the reliable identification of hotspots. Moreover, insight into consumption characteristics is not given and specific energy consumptions of products cannot be derived.[19]

Simulation based approaches require detailed knowledge of the machine structure and simulation expertise, which require specifically trained personnel and enormous effort to derive the specific energy consumption for certain products.[15]

As explained by Li et al., a substantial effort is necessary to set up empirical models of processes in industry as well. This is mainly due to the large number of experiments that need to be conducted in order to derive statistically verified results for various operational parameters.[18]

As outlined in the introduction and in this section, the following requirements have to be met for a successful application in industry:

- Multi-product environment: As one production machine is generally used to process different products, this approach has to ensure that the energy demand for all these products can be derived without measuring every product.
- Accuracy and Insight: The approach has to derive consumption figures which provide the right magnitude and allow the allocation of energy amounts to individual products. Moreover, the method ensures a certain level of insight into the consumption characteristics of a machine to allow derivation of improvements.
- Little effort: Resources like time and personnel are usually limited and an applicable approach must deliver results with little effort and must not require extensive experiments or analyses.
- No expert knowledge: Many SMEs do not have the expertise on energy efficiency of production machines. Thus, the approach must on the one hand provide clear guidelines for the course of action and on the other hand it must not require any prior knowledge about modeling or statistics but just a general understanding of the process.
- Tailored effort: Some processes are more complex than others and feature more variables which have to be considered in the consumption models. The effort for analyses should therefore be geared to the process complexity.
- Transferability: The method must be applicable to a wide range of production machinery, as there is a great variety of machines in industry.

Table 1 summarizes the evaluation of the discussed approaches. None of the existing approaches meets all requirements for a successful application in industry. Therefore, a new, transferable approach is to be developed which balances the effort and benefit of energy consumption analyses in industry.

3. Methodological Approach

The proposed approach aims to predict the electrical energy consumption for an arbitrary product on a specific machine (SEC, specific energy consumption per product). In order to efficiently deal with a diverse range of machines used in the shop floor, the main focus is to keep the measuring efforts as low as possible while delivering a targeted accuracy level over 80 %. Firstly, a decision tree is provided in section 3.1 giving clear guidelines for the machine classification. Based on these, production machines are categorized into four groups according to their energy consumption characteristics. Correspondingly, section 3.2 to 3.5 present the detailed approaches for deriving SEC prediction models of each machine group.

3.1 Decision Tree for Machine Classification

According to the characteristic of the electrical energy consumption, four groups of machines are identified. These are, in order of increasing complexity, Type 1: Simple Machines, Type 2: Adjustable Simple Machines, Type 3: Single-Purpose Complex Machines, and Type 4: Multi-Purpose Complex Machines. The analyses of machines depending on their type are described in detail in the following sections. Since the energy prediction models are highly dependent on the classification, the decision tree in Fig. 1 is crucial to ensure minimal analysis effort. The machines are classified by a quick screening procedure which uses a number of adjustable parameters as decision points. To be more specific, if the machine parameters are fixed, then this machine is classified as a simple machine. If only one parameter is adjusted during the production, this machine is categorized as an adjustable simple machine, otherwise the machine is considered as a

Table 1 Adaptability of existing approaches

Approach	Multi-product Environment	Accuracy and insight	Little effort	No expert knowledge	Tailored effort	Transferability
Exergy	○	◐	◐	○	○	●
Power rating	○	○	●	●	●	◐
Simulation	◐	●	○	○	◐	◐
Empirical model	●	●	○	◐	○	○

Legend: Approach is ● fully, ◐ partially, ○ not meeting the requirement complex machine. To distinguish the complex machines, the number of operations is used to separate them into single-purpose complex machine and multi-purpose complex machine. Notably, the machine classification is always case specific and depends on the machine used. Table 2 shows the exemplary machines in each group for the tested factory case.

For each machine group, a customized procedure for establishing a prediction model is presented in Fig 1. In general, the methodologies for the first two groups are similar resulting in similar energy prediction models. Depending on the characteristic of the energy profile, the energy consumption can either be estimated with an average value or decomposed into repeatable energy consumption components. The components are called energy blocks,[20] which can be aggregated for the total energy consumption of a specific product according to the product characteristics. For the Type 2 Machines, the main difference comparing to the Type 1 Machines is that the model is related to a specific process parameter. Notably, if there is no interrelationship between the adjustable parameter and the energy consumption, the Type 2 Machines will be classified as a Type 1 Machine. For the complex machines, more modeling efforts are required to characterize the relationship between the energy consumption and process parameters. A semi-empirical approach is applied here which avoids long test series. The methodology for the Type 4 Machines is basically the same as for Type 3 Machines: the analysis needs to be repeated for all operation classes which the Type 4 Machine is capable of (see dotted arrows in Fig. 1). The analysis and modeling method is explained in more detail in the following subsections 3.2 to 3.5.

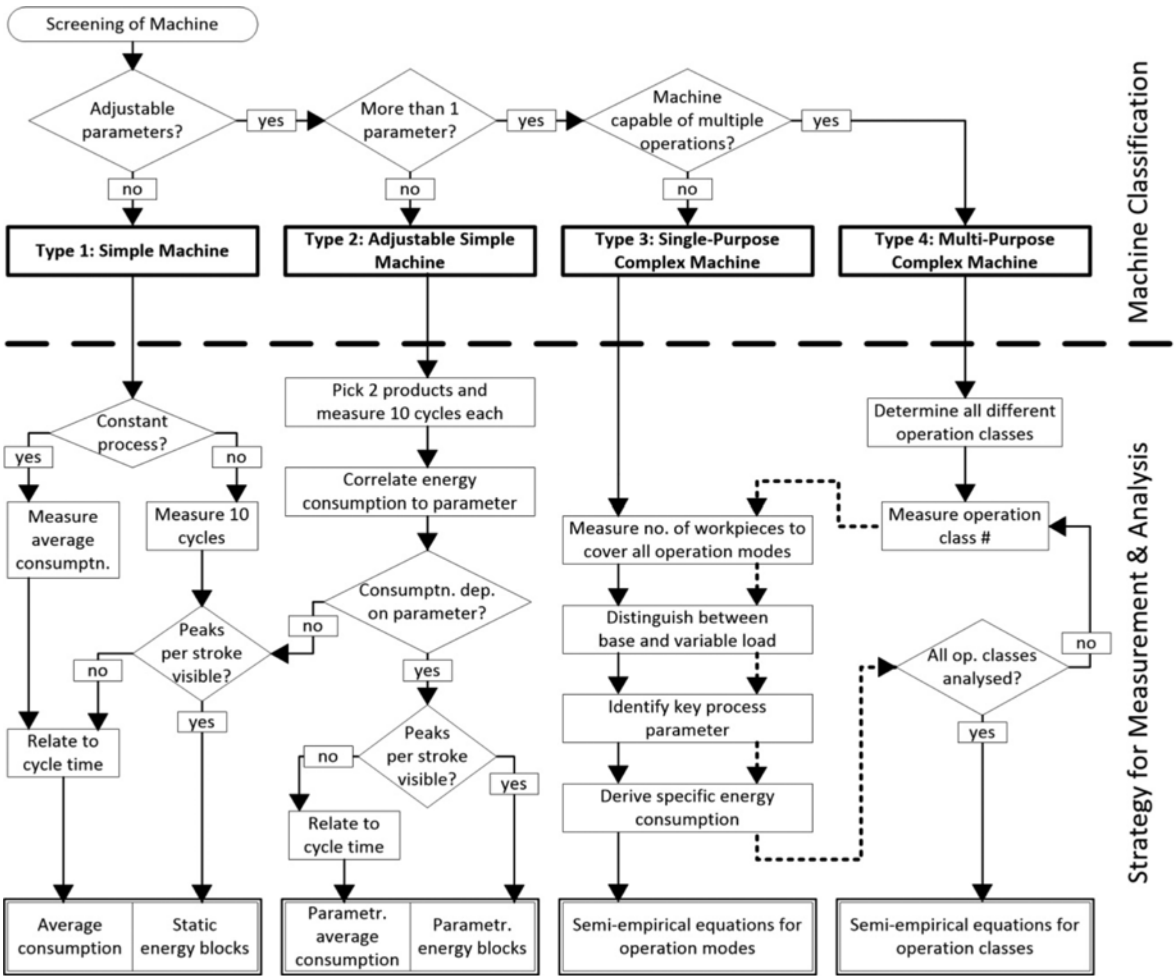

Fig. 1 Decision tree for machine classification

Table 2 Classification of exemplary machines in the tested case factory

Type 1	Type 2	Type 3	Type 4
Annealing furnace Average consumption	Powder glue machine Parametric average consumption (Count of active heaters)	Turning machine Semi-empirical equation (Turning with varying process parameters)	CNC machining centre Set of semi-empirical equations (Equations for each operation class, e.g. face milling, side milling, drilling, and respective operation modes, e.g. roughing, finishing)
Powder coating line Average consumption			
Forging hammer Static energy blocks	Induction heater Parametric energy blocks (Volume of workpiece)	Grinding machine Semi-empirical equation (Grinding with varying process parameters)	
Crank press Static energy blocks			

3.2 Analysis of Type 1: Simple Machines

In general, there are two variations of Type 1 Machines. The energy measurement of the first form shows a constant behavior and does not fluctuate significantly in a repetitive manner during the processing mode (e.g. a continuous furnace). For these machines, the constant power level (P_{avg}) is measured, and then multiplied with the cycle time of the product (t_{cycle}) to derive the energy consumption per product (E_{part}). If a number of parts is processed as a batch (e.g. in a furnace), the energy consumption for the whole cycle has to be divided by the number of parts. In this case, the SEC model requires input information of a standard batch size or a table which lists the number of parts per cycle ($n_{per\ cycle}$) against product type and size. In addition, the cycle time can also be characterized by geometric features of a part (e.g. a linear relationship between cycle time and workpiece length), which facilitates energy consumption predictions for a wide range of products. Hence, the energy consumption per part for this form of Simple Machines can be estimated according to Eq. (1).

$$E_{part} = t_{cycle} \cdot P_{avg} / n_{per\ cycle} \tag{1}$$

In comparison, the other form of Type 1 Machines shows significant fluctuations in the energy profile as depicted schematically in Fig. 2. This behavior is often found among metal forming machines, such as a forging hammer. In industries, the process parameters of these machines (e.g. force, pressure, etc.) are normally kept constant; and, different parts may only require a different number of unit operations, for instance, number of stokes per part during a forging process. From the energy consumption perspective, each unit operation results in a recognizable peak in the energy profile. The area under this peak, or called energy consumption per stroke (E_{stroke}) in this paper, remains approximately constant regardless of the product type. In order to estimate the energy consumption per part for this form of Simple Machines, empirical measurements need to capture a number of peaks to derive the average E_{stroke} as a static energy block.

Apart from the energy consumption for value adding activities, a certain proportion of idle energy consumption has to be assigned to each part due to material handling, positioning, tool change, etc. The idle power level (P_{idle}) normally remains constant, which can be easily obtained after the power measurements.[21] Unfortunately, the idle time per product (t_{idle}) is not directly documented in industries, and it fluctuates from part to part. Alternatively, the cycle time (t_{cycle}) can be used to estimate the idle time by deducting the period of value adding activities recorded in the measurements. As mentioned before, Type 1 Machines feature a repeatable E_{stroke}, so the period of value adding activities equals to the duration of each stroke (t_{stroke}) multiplying with the number of strokes (n_{stroke}). Therefore, the E_{part} can be predicted by composing these energy blocks as shown in Eq. (2). Besides the measurements, the only input information required is the n_{stroke} and t_{cycle}.

$$\begin{aligned} E_{part} &= n_{stroke} \cdot E_{stroke} + E_{idle} \\ E_{part} &= n_{stroke} \cdot E_{stroke} + t_{idle} \cdot P_{idle} \\ \text{with } t_{idle} &= t_{cycle} - n_{stroke} \cdot t_{stroke} \end{aligned} \tag{2}$$

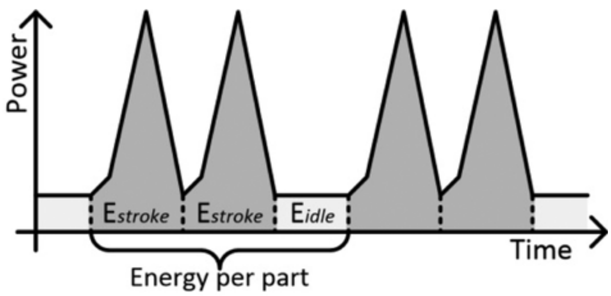

Fig. 2 Power curve of simple machine

3.3 Analysis of Type 2: Adjustable Simple Machines

Type 2 Machines are very similar to those of the Type 1 group. According to the machine classification, the only difference is that one process parameter is modified during the production of different products. Potentially, the power level (P_{avg}) and the energy amount per stroke (E_{stroke}) may vary depending on the modified process parameter. For this reason, two distinct parts with different process parameter settings need to be measured. The consumption figures can then be related to the key process parameter (x) at which a linear relationship is presumed for the sake of simplicity, as shown in Eq. (3). The coefficients (a and b) can be easily derived from the measurements of two distinctive process parameter settings. The rest of the estimation follows the same procedure as in subsection 3.2.

In case the process parameter has insignificant impacts on P_{avg} or E_{stroke}, the decision tree redirects this machine into the group of Type 1 Machines. Although the impacts can only be evaluated after the measurements, the collected data is more than enough to derive static energy blocks as shown in subsection 3.2.

$$\begin{aligned} E_{stroke} &= a_1 + b_1 x \text{ or} \\ P_{avg} &= a_2 + b_2 x \end{aligned} \tag{3}$$

3.4 Analysis of Type 3: Single-Purpose Complex Machines

This group of machines is characterized by the fact that its process can be affected by the adjustment of various process parameters. As mentioned before, a semi-empirical approach is applied for this group to minimize the modeling efforts as well as to provide reliable characterization between the process parameter and energy consumption. Both exergy framework and previous empirical models suggest that a compound process parameter, such as material removal rate (MRR) or throughput, is the decisive factor for the specific energy consumption of a given machine.[16] This finding forms the foundation of the following analysis.

For the purpose of an easier understanding, a turning machine is selected to explain the analysis method of Type 3 Machines. According to their MRR, different operation modes are classified, for example, roughing and finishing as shown in Fig. 3.

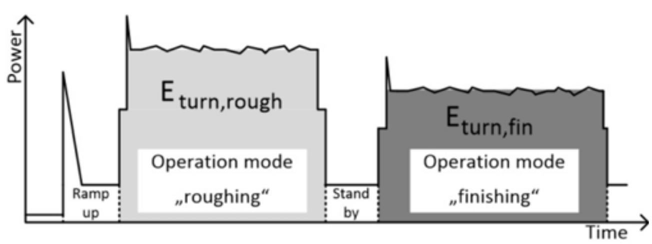

Fig. 3 Schematic power curve of a turning process

For each operation mode, the energy amount E_i can be directly derived from measurements as the shaded area underneath the power curve in Fig. 3. The volume of machined material (V) can be determined according to the product design (e.g. CAD drawing). Then, the specific energy consumption (SEC) for the i^{th} operation mode e_i [Wh/cm^3] can be derived according to Eq. (4). If it is possible to obtain a number of samples for the same operation mode, an average SEC value is preferred to achieve a higher accuracy of energy consumption prediction.

$$e_i = \frac{E_i}{V} \tag{4}$$

Notably, the SEC has to be derived for every operation mode as it strongly differs and, moreover, different geometric variables might be suitable for different modes. For example, the machined volume is used for roughing operations whereas the machined surface could be used for finishing operations due to the small depth of cut. However, it should always be a geometric characteristic of the workpiece. This allows the prediction of the SEC by just comparing the raw part with the finished workpiece. Furthermore, the workpiece material can potentially influences the process rate as well as the specific cutting energy, so the analysis is recommended to repeat for each material in order to improve the reliability. It is important to know that this approach includes simplifications which are responsible for deviations of predicted values from the real ones. However, it will provide the right magnitude as is proven in the case study (see subsection 4.3).

3.5 Analysis of Type 4: Multi-Purpose Complex Machines

The Type 4 Machines allow multiple parametric operations like those of the Type 3 Machines. A schematic power curve for two different machining operations on a CNC machining centre is depicted in Fig. 4. The power levels vary significantly for different operation classes (e.g. turning, milling) and their respective operation modes.

For this reason, the approach of subsection 3.4 is repeated for every operation class the machine is capable of. Additionally, static energy consumption figures, e.g. for tool exchanges, can be derived from the measurements. The result is a set of semi-empirical equations for the prediction of the SEC of arbitrary products on the machine, if the single manufacturing processes are known.

3.6 Energy Consumption on Factory Level

The above SEC prediction models are developed from a unit process perspective to quantify the energy consumption of producing one product. This enables the assessment of the product carbon footprint and the identification of relative energy intensive processes. However, if just a small number of the respective product is manufactured, the hotspots identified might have just a little

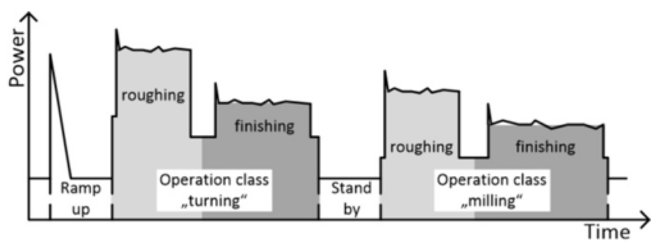

Fig. 4 Schematic power curves of multiple machining operations

importance in relation to the factory's total energy consumption. Thus, investments into improvement measures might not pay off.

To verify the relevance of hotspots, their power level and their annual runtime have to be taken into account concurrently. This follows the idea of establishing energy portfolios proposed by Thiede et al..[4] There are generally two options to determine the relevance of a hotspot. The selection of these two options depends on the number of different products or product families being produced in the company.

If the number of different products is small, the effort for deriving the specific energy consumption for each product is relatively small as well. The result is a database which contains the SEC for each product during each process step. To verify the relevance of one of these process steps, the SEC for each of the m products going through this process has to be multiplied with the annual number n_i of the respective product:

$$E_{annual} = \sum_{i=1}^{m} (n_i \cdot SEC_i) \tag{5}$$

In many cases however, there is a large number of different products. Deriving the SEC for each of them might not be suitable therefore certain key products have been analyzed. Still, this is sufficient data to assess the relevance of machines, if their annual runtime is recorded in the company's ERP system (Enterprise Resource Planning). It is assumed that the consumption characteristics of the regarded machine differ only slightly for different products. The machine's average power level in production mode can then be derived by dividing the SEC of the key product by its cycle time t_{cycle}. This value can be multiplied with the annual runtime of the machine $t_{annual,run}$. If additional data such as annual setup times $t_{annual,setup}$ are available, it can be multiplied with an appropriate consumption figure (idle power P_{idle} in this example). The following equation shows the derivation of the machine's annual consumption:

$$E_{annual} = \frac{SEC}{t_{cycle}} \cdot t_{annual,run} + P_{idle} \cdot t_{annual,setup} \tag{6}$$

Applying one of these two methods allows the identification of energy hotspots in production with simple calculations based on the prior measurements. If improvement potentials have been identified, resulting savings can be appraised using the same equations. This provides the basis to assess the return of investments for energy efficiency measures.

4. Application in Case Study

The methodology was employed in a case study at an Australian manufacturing company that produces products for the electricity network. This company is organized according to the job-shop principle and manufactures a large variety of different products, most of which in batch production. All 33 production machines (excluding duplicate machines) were analyzed by applying the presented methodology. Resulting machine models were used to derive the SEC of seven key products which represent the most important product families. Exemplary machines of Type 1, Type 2, and Type 4 are presented here whereupon the analysis of the Type 4 machine automatically covers Type 3 machines.

4.1 Type 1: Simple Machines

Two machines are presented here to cover both the analysis using average consumption with cycle times and the analysis with static energy blocks.

The powder coating line is used for coating server racks. Parts are hung on a conveyor which constantly transports them through a washing booth, a drying oven, a spraying booth and a curing oven. The conveyor can accommodate 55 parts and it takes 2.5 hours for one part to go through all process steps. (figures changed for confidentiality reasons). After ramp up, the machine runs at a constant power level which only changes slightly if a manual spray booth is used for special colors instead of the auto spray booth. So the average consumption $P_{coat,avg}$ is charged against the cycle time of one product (place on the conveyor) to receive the SEC:

$$E_{per\ part} = P_{coat,avg} \cdot \frac{2.5h}{55\ parts} \tag{7}$$

The forging hammer as the second Type 1 Machine performs countable strokes in the form of hammer blows, which cannot be adjusted in any way. Fig. 5 shows the measured power curve for the production of eight parts which require three hammer blows with an averaged energy amount E_{stroke} per blow. Each blow takes 3 sec and after performing the three blows, the power drops to the idle level P_{idle}.

With these energy blocks, the energy demand for an arbitrary product on the forging hammer can be predicted by using Eq. (2). The only facts to be known about the product are the number of strokes necessary and its cycle time.

4.2 Type 2: Adjustable Simple Machines

Two representatives from the second group of machines are presented here. For the first machine, the adjustable average consumption method is employed while the second machine is modeled with parametric energy blocks.

The company's powder glue machine is used to agglutinate sets of wire. Those are put on a conveyor and go through powder spray nozzles and then through a heating and cooling zone. Depending on the length of the wire sets and the rigidity demanded, between four and six nozzle-heater units are active. Two runs were measured (five units vs. six units active); results and the derived equation for predicting the power level are shown in Fig. 6.

The product cycle time can be derived from the lot size as the conveyor works at a constant pace. As soon as the last wire on the conveyor has left the heating zone, the heaters are turned off but the machine is still running at base load until the last wire has reached the end of the cooling zone. This behavior was considered in the derivation of the machine model. However, for the sake of simplicity, a standard lot size was assumed.

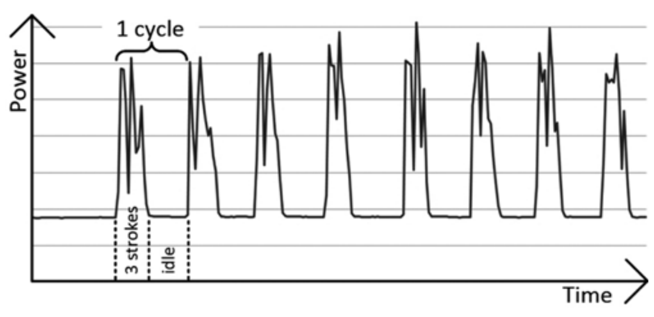

Fig. 5 Power curve of forging hammer

The induction heater is modeled using parametric energy blocks. It was found that the power level in the heating process and the duration for one part could be adjusted. Both factors together determine the amount of energy going into one product and this in turn is contingent on the material volume. It was not necessary to investigate the behavior for different materials as only steel parts are heated. Thus, the workpiece volume was chosen as key process parameter and two different workpieces were measured so that the energy demand per cm³ (e_{heat} [Wh/cm^3]) of material could be derived. Between two products, the power drops to the idle level for one second for any product so that the cycle time does not have to be considered. Instead, a fixed energy amount E_{idle} is used.

$$E_{part} = E_{idle} + V_{part} \cdot e_{heat} \tag{8}$$

4.3 Type 4: Multi-Purpose Complex Machine

A CNC machining centre was also analyzed using the proposed methodology. The measurements were carried out with a workpiece that requires all the different operation classes the machine is capable of. Fig. 7 shows the respective power curve progressions.

The following set of equations (see Table 3) was derived for the different operation classes. Operations are sorted according to their key process parameters (depth of bore, volume, area). Drilling and threading both cause similar consumption behavior that mainly depends on the depth of bore/thread while the diameter has hardly any influence. For each bore, the energy amount for the spotting operation ($E_{spotting\ point}$) has to be added. In case both face and side milling are involved at once (shoulder or channel milling), the average specific consumption ($E_{rough\ face\ \&\ side\ mill}$) must be taken. Whenever a tool change is necessary, $E_{tool\ exchange}$ has to be added.

With the given set of equations, the energy demand for an arbitrary workpiece (which is of the same material) can be predicted, if its raw part and its finished shape are known. This is necessary to derive the amount of material machined. For validation purposes, the prediction was done with a randomly picked part. All energy amounts for the different operations were predicted using the given equations. The whole process was measured and required 160.31 Wh from beginning to end (see Fig. 8). The energy amounts for single operations 1 to 4 were extracted from the measurements and include the respective tool exchanges. Table 4 compares the prediction and measurements. It can

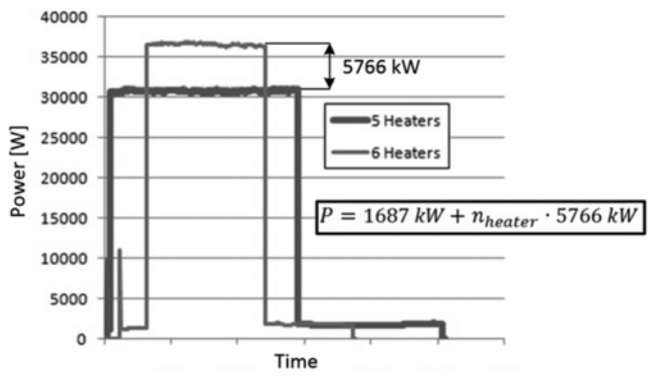

Fig. 6 Powder glue machine. 5 vs. 6 active heaters

be seen, that even with the massive simplifications the right magnitude can be predicted which is notable because the effort necessary is quite small.

The benefit can be seen by comparing this predicted value of 181.01 Wh to the prediction based on power ratings as proposed in [4]: The machining centre has a rated power of 20 kVA. The whole process takes 420 sec including the idle time for re-clamping. This would result in a predicted value of 2,333 Wh which is 13 times higher than the actual consumption. This comparison shows that the presented model provides much better accuracy with a moderate effort.

4.4 Energy Consumption on Factory Level

A factory hotspot analysis was carried out according to subsection 3.6. Thus, all machines which contribute significantly to the total energy demand of the factory were identified so that goal-oriented improvement measures with a big leverage effect could be employed. Wherever investments were necessary, their amortization could be validated by charging them against annual savings.

Fig. 9 shows the difference between the SEC (Energy per Part) and the machines' annual demand (Energy per Year). For reasons of confidentiality the shares of the five machines relative to each other are given. It is also important to know that values refer to different workpieces. The graph highlights the importance of considering not just the SEC but also the runtime of the machine.

Table 3 Semi-Empirical equations for tested CNC machining centre

Equation	Key process param.
$E_{bore/thread} = h_{depth}[cm] \cdot 2.76\frac{Wh}{cm}$	h_{depth} (depth of bore/thread)
$E_{spotting\ point} = 1.34Wh$	
$E_{rough\ face\ mill} = V[cm^3] \cdot 0.525\frac{Wh}{cm^3}$	V (Volume machined)
$E_{rough\ side\ mill} = V[cm^3] \cdot 1.383\frac{Wh}{cm}$	
$E_{rough\ face\ \&\ side\ mill} = V[cm^3] \cdot 0.954\frac{Wh}{cm^3}$	
$E_{finish\ face\ mill} = A[cm^2] \cdot 0.069\frac{Wh}{cm^2}$	A (Area finished)
$E_{finish\ side\ mill} = A[cm^2] \cdot 0.169\frac{Wh}{cm^2}$	
$E_{tool\ exchange} = 8.10Wh$	

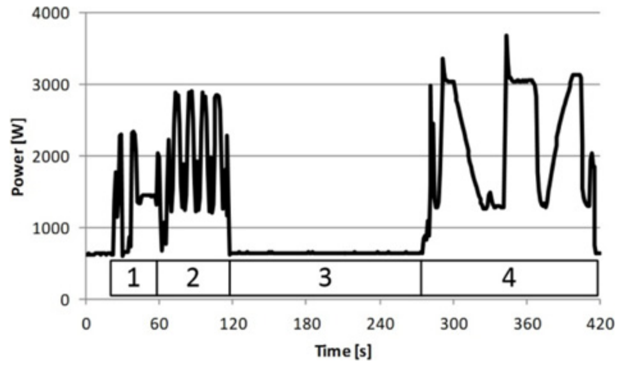

Fig. 8 Validation measurement with marked process steps

Table 4 Comparison of prediction vs. measurement

#	Operation	Pred. [Wh]	Meas. [Wh]	Difference
1	tool exchange: side miller*	8.10	13.60	+4.6%
	fin. side mill. A = 18,1 × 2 cm^2 = 36.2 cm^2	6.12		
2	tool exchange: drill Ø18*	8.10	30.18	+17.8%
	4× spotting point	5.36		
	4× bore (h = 2 cm)	22.08		
3	idle for re-clamping (150s)	27.42	28.20	-2.7%
4	tool exchange: side miller*	8.10	85.72	+21.1%
	rough side & face mill.: 2× channel (V = 2 × 25.38 cm^3) + rough side mill (V = 1.5× 11.4 × 2 cm^3 = 34.2 cm^3)	95.73		
	Whole process	181.01	160.31	+12.9%

* Tool ex. not explicitly measured but included in following operation

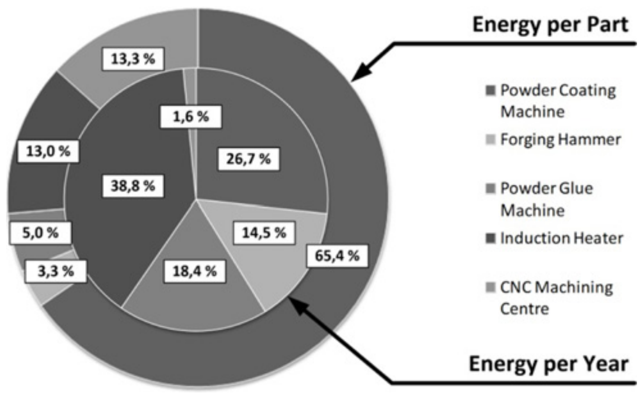

Fig. 9 Hotspot identification

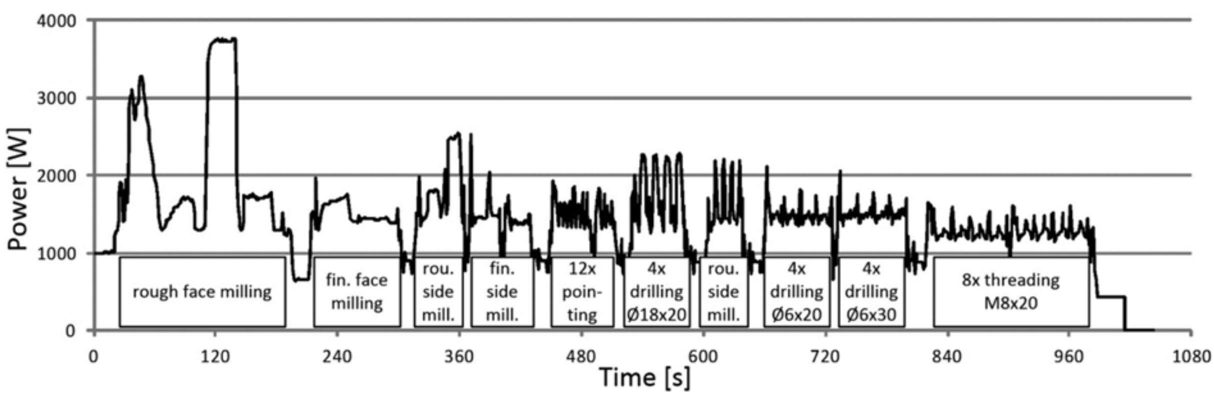

Fig. 7 Power metering of CNC machining centre

5. Discussion, Summary and Outlook

The proposed methodology presents an energy consumption prediction methodology, which is easy to use and less time consuming than empirical models, and superior than the estimations based on power ratings (see Fig. 10). The methodology presented here requires a little effort in the beginning which is higher for complex machines than for simple machines due to the more complex analysis. After this initial step, the large benefit of the methodology lies in the very little effort (comparable to estimation based on nominal power ratings) that is needed to predict the energy demand for future products. Measuring each product provides 100% accuracy but requires a significant effort for each product. This assessment shows that the proposed methodology closes the gap between the rough estimations with little effort and the highly accurate empirical models requiring big effort.

A comprehensive methodology was developed to gain transparency of energy consumption in manufacturing companies. Guidelines allow customized analyses of machines to keep the effort low. Generally, just one product needs to be measured to set up the machine model. This model can then be employed to predict the SEC for other products being manufactured on the respective machine. Hotspot machines which contribute significantly to the total energy consumption of the factory or to the product carbon footprint can be identified accurately. As conducted measurements provide detailed insight into machines' consumption characteristics, goal oriented improvement measures can be derived.

Further steps might be the inclusion of additional energy carriers like compressed air, steam and cooling water. Moreover, material data of products could be collected. This would allow creating an energy and material flow model of production sites in e.g. Umberto software. Then, the carbon footprint of the products can be derived precisely. Additionally, effects of improvement measures on the ecological performance of the production could be quantified.

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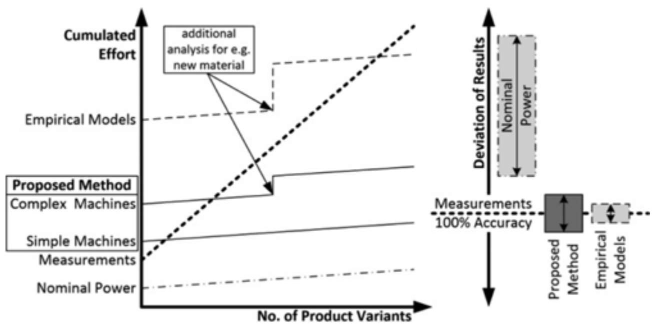

Fig. 10 Assessment of effort and accuracy

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