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Advanced energy data analytics to predict machine overall equipment effectiveness (OEE): a synergetic approach to foster sustainable manufacturing.

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Abstract

Understanding the relation of production activities and energy demand is of crucial importance for fostering sustainable manufacturing. While so far the perspective is mainly on augmenting production data with energy related aspects, this paper suggests an alternative approach to overcome current challenges. Energy data is the starting point and shall be utilized for the prediction of the overall equipment effectiveness (OEE) which is an established and comprehensive indicator for machine performance. Based on a common underlying definitory framework, two alternative prediction methods are presented. Results indicate that an energy based OEE prediction is actually possible with reasonable accuracy and effort.

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Keywords: Energy efficiency, Machine, Overall Equipment Effectiveness (OEE)

1. Introduction

The latest IPCC report emphasized once more the necessity to push forward efforts towards environmental sustainability. Manufacturing is the sector with highest contribution to e.g. greenhouse gas emissions (GHG), largely driven by energy demand [1]. In both research and industrial practice, an increasing amount of activities addressing this challenge could be seen in the last years [2]. These comprise of e.g. fostering energy efficiency or substitution of energy carriers towards more sustainable (renewable) sources. But still those efforts are not enough and certainly dealing with energy demand is still not of highest priority in the majority of manufacturing companies [3]. Whereas the environmental relevance is clearly given, one major barrier is still the limited economic return on investment, even in recent times of rising energy prices in many countries. Efforts for energy related analysis and improvement can be high but potential cost savings are limited, e.g. in comparison to other cost factors (e.g. material, personnel) [3]. As indicated in Figure 1, energy demand of e.g. machines is of course a direct result of production related activities (upper loop in Figure 1). Machine configuration (e.g. machine components and their interaction) and operation (e.g. production schedule, applied control regimes) will eventually lead to a specific machine energy load profile. Thus, energy demand patterns can be brought in relation to production activities. Given that synergy, approaches to connect conventional production key performance indicators (e.g. related to output, time and quality) with energy considerations are in general interesting to get more insights while avoiding additional data acquisition efforts.

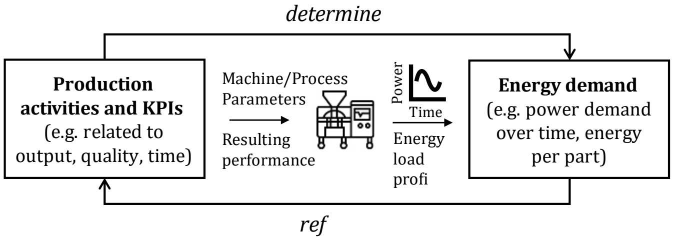

Figure 1: Relation of production activities/performance and energy demand.

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The focus of manufacturing energy related approaches so far is on augmenting production parameters and resulting performance with energy demand, e.g. in order to understand, assess and eventually improve the energy demand of manufacturing processes and systems [2]. However, little attention was spend so far on the other side of the same coin: obviously the energy demand of a machine is a state variable that is rather simple to acquire and potentially reflects nicely and in real time what is currently happening (lower loop in Figure 1). The question is whether and what can be learned about the production performance just from a closer look on energy data of manufacturing machines and potentially systems. While similar approaches can be found e.g. for condition monitoring of technical equipment [4], a perspective on utilizing this data for reflecting production performance is missing so far. A couple of potential benefits directed towards more environmentally and also economically sustainable manufacturing are connected to such an approach:

- real time information of actual, operational data is interesting for different applications to improve production
- an energy sensor is cheaper compared to more sophisticated production data acquisition (PDA), especially for more complex key performance indicators like the overall equipment effectiveness (OEE)
- energy metering points can be implemented as external sensor and do not require any connection to the control of the machine – given that, it is also applicable for machines that are not connectable on other ways (e.g. retrofitting)
- inherent connection of economic and environmental issues which enables an integrative consideration without further efforts. An added value of energy data acquisition would certainly push forward broader coverage and improvements toward sustainability
- significantly more transparency on energy demand patterns would be achieved which open ups new opportunities for energy efficiency benchmarking and improvements.

Against this background, this paper aims at investigating opportunities and limitations of solely using energy data for analyzing production performance. The focus will be on single production machines and on the overall equipment effectiveness (OEE) as one of the most comprehensive and established key performance indicators (KPI). As indicated, there are numerous interesting approaches that investigate the relation of production performance (e.g. expressed through OEE) and resulting energy demand/efficiency of machines. However, the novelty here is to flip that principle and use energy data to estimate the OEE for addressing the aforementioned potential benefits. After giving relevant background, the paper will introduce the methodology before illustrating the implications in selected case studies.

2. Technical background and research demand

2.1 Energy demand in manufacturing

As indicated, nowadays various activities around energy related considerations in manufacturing can be found, comprehensive overviews are available in [2] and more recently in [5]. Typically activities can be distinguished in terms of their area of investigation (e.g. machine, manufacturing system/factory, supply chain) and the addressed technological or methodological approach, e.g. for systematic measurement, assessment and analysis [6] [7], modelling and simulation (e.g. state based [8] or empirically [9]), benchmarking (for machine tools, e.g. [10]) and finally deriving and implementing improvement actions (for machine tools, e.g. [11], for manufacturing systems e.g. [12]). Those important contributions bring together production with energy data in planning or operation phase. Finally, the objectives are to improve the energy efficiency or energy flexibility [13] of the considered machine or system and/or enable an energy assessment of production related measures.

2.2 Overall Equipment Effectiveness (OEE) and energy data

The Overall Equipment Effectiveness (OEE) is a very established key performance indicator that reflects the performance of a production machine in comprehensive manner. The OEE was introduced in the 1980s from Nakajima [14] in context of lean manufacturing. It integrates six big losses of manufacturing machines in one indicator as multiplication of three different components (Figure 2): availability reflects the stoppage of machines due to unplanned failures and setup times. While the machine is in general working, the performance rate takes into account inefficiencies through unnecessary idling or minor stoppages as well as reduced speed which eventually still leads to less output as possible. Finally, the quality rate reflects whether the product output is conform with the necessary specifications. The OEE is widely adopted in industry and also ongoing subject of research for further development.

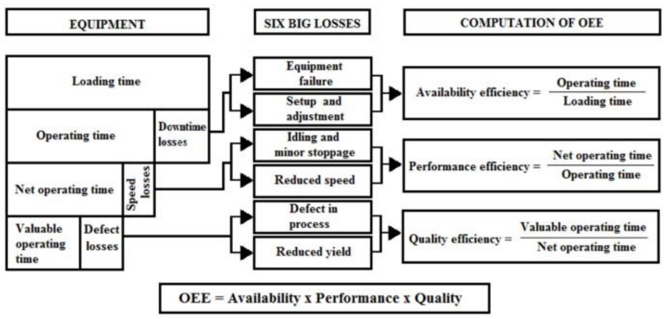

Figure 2: Structure of Overall Equipment Effectiveness (OEE) [14].

However, very few approaches explicitly deal with the relation of OEE and energy demand so far. Barletta et al. [15] developed an interesting approach which orients on the general structure and idea of the OEE in order to assess the energy efficiency of a manufacturing system (based on data derived from discrete event simulation). Also other authors [16][17] investigate and actually model the relationship of energy and OEE in order to predict energy demand and identify energy efficiency improvement potentials. All these approaches give interesting insights and especially [15] provides some very relevant background for defining the relation of OEE and energy indicators. However, their starting point and perspective is from OEE towards resulting energy demand and not the other way around as intended here. This contribution aims at predicting the OEE of a machine based on the metered energy data.

2.3 Research demand

Considering manufacturing energy demand is a topic of strong interest and numerous important contributions have been published and implemented. Often an integrated consideration on both production performance and energy demand is already pursued, e.g. when improving energy efficiency in design or operation through appropriate production models (of machines or systems). Thus, the perspective so far is typically from production towards resulting energy demand so at least some kind of production related input data is necessary. This paper turns that around and takes on a new perspective – the focus is on energy data as starting point. Ideally just based on that, production performance expressed through the OEE shall be estimated in order the seize the potential benefits as introduced in section 1. Therefore, fundamental understanding about this relation and the development of an appropriate methodology is necessary.

3. Predicting OEE through machine energy data

3.1 General approach and concept

As introduced, the overarching objective is the utilisation of machine energy data as base for an assessment of production performance. Just through energy data and ideally without prior knowledge about the machine, the OEE as comprehensive machine KPI shall be estimated. Thereby, different advanced analytics methods will be applied for energy data. Advanced analytics refers to “the autonomous or semi-autonomous examination of data or content using sophisticated techniques and tools, […] to discover deeper insights, make predictions, or generate recommendations.” [18] In context of this paper, statistical methods, state based pattern analysis but also machine learning approaches will be used. Obviously an energy load profile (electrical power over time) of the production machine is the necessary starting point. Electrical load profiles can be acquired through either fixed installed or mobile standard metering equipment, on machine level typically with temporal resolutions of one or several seconds up to minutes [7]. This data needs to be brought together with the OEE components. Figure 3 illustrates the underlying methodological approach which bases on the definition of clear machine states. According to VDMA guideline 34179 [19], four main states are distinguished here: *off* (machine is completely switched off), *standby*/idle (certain components are on but machine could not produce yet), *operational* (ready for operation) and finally *working* (processing). Additionally, short time *peaks* might occur e.g. when ramping up machine components and switching between machine states. Many production machines show related energy load profiles, for the specific case this could certainly also mean that e.g. one state is missing or even there are e.g. several working states. Altogether, this approach allows an appropriate characterisation of machine states and was also picked up by industry already [20]. As already pointed out by many authors [8][10], machine states eventually determine a certain energy demand (either rather constant or in a range). To now establish the connection of energy to the OEE, a clear allocation of those defined machine states to the OEE components is suggested (see also [15]). In accordance with the original OEE definition, *standby* and *off* states are connected to the availability component since they reflect larger failures and also setups. In contrast to that, states *working* and *operational* are allocated to the performance component – with that, the impact of idling and shorter stoppages is incorporated. Also occurring peaks are allocated to the performance components since they reflect non-value adding states of a machine. The quality rate is certainly a special case: it is indirectly coupled to the working state since the total output is determined here. There are indeed cases where occurring quality errors can be seen in the electrical load profile, e.g. through deviations from expected processing power or shorter cycle times. But since that can hardly be generalised calculating that specific OEE component will be considered as an external manual input (if of detailed interest). However, this is a valid limitation since product quality is typically determined anyway.

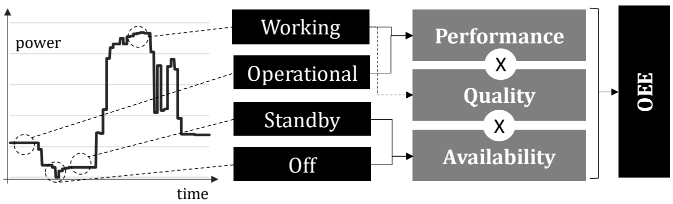

Figure 3: Allocation of machine states to load profile and OEE.

Based on energy load profiles as necessary base and the introduced general understanding of the relation of machine states and the OEE components, two different approaches are distinguished for the energy based OEE prediction (Figure 4). The state based calculation focuses on discriminable machine states and takes into account the frequency of occurrence. The machine learning based prediction utilises statistical features of the load profile. Eventually, both approaches can be used to predict performance and availability components of the OEE.

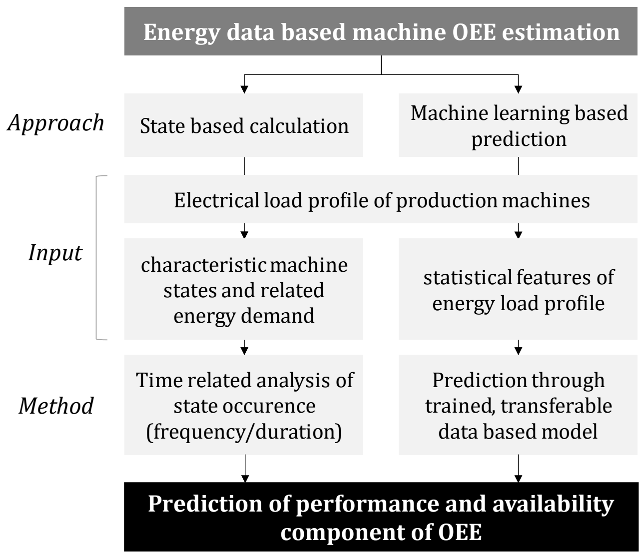

Figure 4: Overview and comparison of considered approaches for energy data based OEE prediction.

3.2 State based OEE calculation

The previous section laid the ground with the defined allocation of machine states (and therewith energy demand) to OEE components. Given the overarching objective that just energy data shall be used, a computational methodology for the automated identification of machine states through energy data is necessary. Therefore, an approach introduced by Labbus et al. is utilised [20]. As shown in Figure 5, frequency analysis of energy data can be used to identify the typical machine states, leading to unique fingerprints that characterise the machine and its modes of operation in the considered time frame. Through mathematical transformation of the histogram (e.g. with Kernel density estimation) the automated derivation of energy values for machines states is possible. The applicability and good accuracy for a wide range of production machines was shown in [20][21]. Figure 5 shows several examples for machines with different energy load patterns which clearly lead to characteristic density diagrams with discriminable machine states.

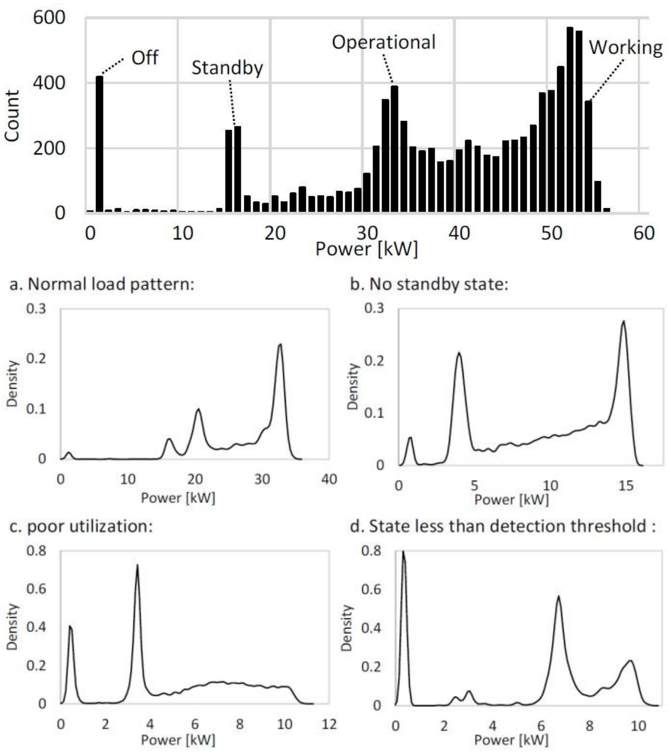

Figure 5: State identification with energy based frequency analysis, general principle and examples for different load patterns [20].

To eventually calculate the OEE time shares of the different machine states are necessary – those can be directly gathered from the histograms/density diagrams simply through multiplying the frequency of occurrence for the respective state with the temporal resolution of the measurement. In the example of Figure 5 that would e.g. mean that the value representing the *off* state occurred around 400 times – multiplied with the temporal resolution (TR) for one measuring point (e.g. 15min) that leads to 6000 hours in the considered total time frame. In general, with occ_i describing the number of occurrences of the states and TR reflecting the temporal resolution, the state based OEE calculation can be expressed as:

$$(1) \quad OEE = (total\ time - occ_{off} * TR - occ_{idle} * TR)/total\ time * (occ_{working} * TR/(total\ time - occ_{off} * TR - occ_{idle} * TR)) * quality\ rate$$

The example in Figure 5 (with temporal resolution of one hour per measurement) also clearly shows one main challenge related to this approach: due to fluctuation of energy demand but even more due to occurrence of several machine states in one measuring point, the energy data may be blurred and not as distinctive as wanted. Figure 6 exemplary illustrates this effect for a specific example of a punching machine. While the overall average power demand stays the same, rougher temporal resolution lead to less detailed representation of the energy demand over time. Thus, also the identification of the occurring machine states and therewith the correct calculation of the OEE is impeded. To overcome this challenge, two measures are recommended: on the one hand, measurements with a temporal resolution of ideally one second but not definitely not than the cycle time of the machine/process should be used. On the other hand, the definition of not just single energy values but rather a certain range of values for representing respective machine states is suggested. Figure 6 illustrates this procedure while using defined value ranges in order to estimate respective time shares of the machine states.

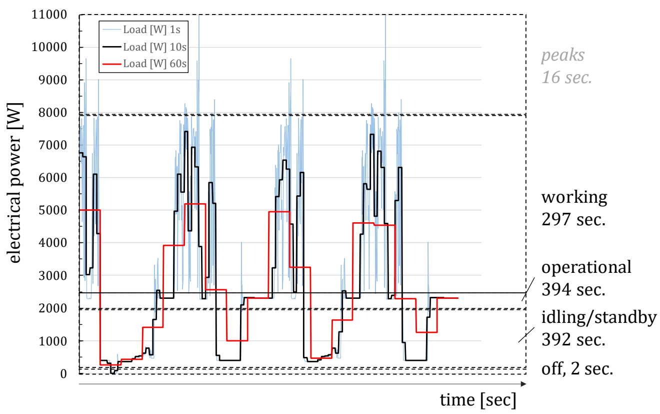

Figure 6: Exemplary machine load profile with different temporal resolutions, allocation of machine states and related time shares.

3.3 Machine learning based OEE prediction

The state based OEE calculation is a straight forward and - if properly set up - rather accurate way to predict the OEE of machines through energy data. However, an alternative and quite promising way would be the prediction purely based on the statistical characteristics of the measured energy data. Therewith, the step of identifying and allocating machines states could be avoided. In order to investigate the fundamental relations and the feasibility of such an approach, a large variety of different cases with differing energy and production data is necessary. Therefore, a model based load profile generator was developed: based on the general understanding as presented in section 3.1, dedicated load profiles and also the related OEE can be calculated. Monte Carlo simulation is applied with stochastic variation of energy demand and time shares for different states, leading to over 2000 scenarios with unique load profiles each for a virtual production time of around 5 hours. For each scenario the statistical characteristics of the resulting load profile (e.g. average, standard deviations, skewness) were computed, normalized (e.g. referring to maximum load in load profile) and are finally represented as one data point as base for the following analysis. Figure 7 shows some exemplary results which underline the unique and interesting relations of some statistical indicators with the OEE. Selected statistical indicators were used to set up prediction models (with regression and artificial neural networks/ANN), first based on the whole diverse data set. Figure 7 (b) underlines the general predictability of the OEE but there of course also deviations subject to the broad approach of the generic dataset. Given the encouraging results, also more machine specific models were built up. Therefore real machine states and energy data was used but production scenarios were again stochastically varied in order to generate load profiles that cover a large range of circumstances. This data was again used to train regression and ANN models - Figure 7 (c) exemplary shows the (test data) results for a specific model (again related to the machine also shown in Figure 6). While again just statistical indicators of the load profile are used here, a nice fit can be observed. However, this is based on simplified underlying machine models, more detailed and realistic machine studies need to be conducted to further confirm this potential.

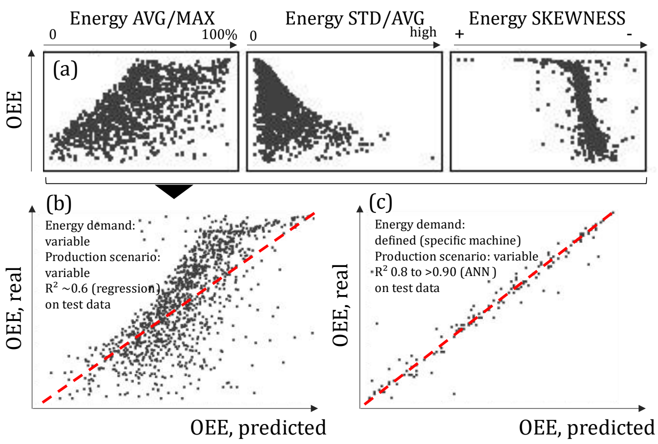

Figure 7: Relation of selected statistical indicators to OEE (a) and results of prediction models for generic (b) and machine specific (c) case.

4. Application

Finally, the presented approaches are applied to different real production machines. These are of course just examples but with a punching machine, a CNC machining centre and textile weaving machine already a certain range of machine classes with very different characteristics are reflected. Table 1 gives an overview of the results, for the punching machine also in relation to different temporal resolutions as introduced in Figure 6. The results underline their influence and the favourability of more detailed energy measurements. As clearly visible and expected for the example of the punching machine (as introduced before, short process times of few seconds), results get significantly more inaccurate if TR of e.g. 60 seconds. Machine learning approaches are even not applicable anymore since not enough statistical features can be discriminated in the data.

*Table 1: Exemplary results of considered case studies (*TR not sufficient for machine learning based approach).*

	Punching machine (sheet metal)			CNC-M	Weaving
	TR 1s	TR 10s	TR 60s	TR 1s	TR 1s
(A) Availability	62,9%	61,7%	61,1%	96,0%	97,0%
(P) Performance	46,9%	57,6%	72,7%	27,5%	80,1%
(Q) Quality	100,0%	100,0%	100,0%	100,0%	100,0%
OEE (state alloc.)	29,5%	35,5%	44,4%	18,4%	77,7%
Difference		*8,7%*	*21,6%*		
OEE (ANN)	*18-27%*	*26-30%*	*-**	*11-15%*	*62-79%*
OEE (regression)	*26-32%*	*33-40%*	*-**	*21-27%*	*52-62%*
OEE (measured)	**31,5%**			**15,5%**	**75%**

The state based allocation (based on TR of one second) turns out to provide a robust and promising OEE estimation, acceptable deviations occur due to faulty incorporation of e.g. transition between states. The separate consideration of availability and performance gives interesting insights towards root causes and fields for improvement from both OEE and energy related perspective. Based on the procedure described in 3.3, different configurations of machine learning approaches (with multi-variate regressions and neural networks) were applied as well. The range of results underlines the applicability and potential but also less accuracy compared to the state based allocation. However, many directions for further improvement (e.g. identification of more features, specific machine models – so far just based on generated load profiles) are available and, given the simpler application procedure, are also worthwhile to be followed up.

5. Summary, discussion and outlook

This paper takes on an unique, alternative perspective on energy demand and production activities while aiming at utilising energy data for the prediction of the overall equipment effectiveness. Based on a defined underlying understanding, two alternative methods are presented. Results indicate that an OEE prediction is possible with reasonable accuracy and effort. Both methods are automatable, easily implementable (also as retrofitting) and foster understanding and improvements of production machines. With this accessible and deeper insight also advanced benchmarking functionalities are enabled. As intended, the approach brings economically and environmentally driven activities closer together. With its added value, the spread of energy transparency measures in industry is facilitated.

While applicability is given for a wide range of machines, there are of course also clear limitations. The natural focus is on machines with discriminable machines states that are actually reflecting production status and result in reproducible energy demand. Therewith, applications in e.g. process industry or with more continuously operating equipment (e.g. ovens) are limited. The state based approach inherently provides good accuracy in OEE prediction but requires an additional step for state recognition. The machine learning approaches bear even broader application potential but further work to improve accuracy and robustness needs to be done. Thus, next steps will deal with the identification of more features for data analysis and extension of case studies to derive more dedicate models but also inherent limitations.

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