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STUDY ON THE LOAD PROFILE CHARACTERISTICS OF MACHINE TOOLS IN MACHINING OPERATIONS

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Abstract

Due to rising costs and the need for a more sustainable use of resources, there is an increasing focus on energy use in industrial production. As a result, energy-related data, for example from machine tools, is increasingly being collected. In addition to information for the energy evaluation of individual systems and processes, load profiles of machine tools offer further opportunities for process monitoring, such as tracking of production lots. As sensors for electrical power monitoring can be retrofitted without interfering with the process or the machine control unit, load profiles offer a cost-effective data source for data mining and machine learning applications. In order to support the generalisability of such applications, this paper describes the load profiles of machine tools and presents an overview on characteristics and the variety of load profiles of turning, grinding and milling machines in industrial use cases. Load profiles of 18 machine tools from machinery, automotive and aerospace production were analysed with regard to statistical characteristics during machining cycles. In particular, typical value ranges and statistical figures of load profiles and the influence of the sampling rate on the time series are presented.

Keywords:

Load Curve, Power, Time Series, Machining

1 INTRODUCTION

As it is estimated that machine tools account for 5-10% of the global electrical energy demand of the metal-working industry [Denkena 2020], the evaluation of the energy-related data of machine tools is a relevant aspect of the transformation towards a more sustainable industry.

In addition, energy-related data from machine tools is a useful source of data to obtain information about processes. Previous work has shown that electrical load profiles of machine tools or machine components can be used for various applications. If energy-related data, such as the current of the spindle of a turning machine, is available at high frequency, it can be used to identify faulty workpieces during machining [Fertig 2020]. On the other hand, the load profile of a machine makes it possible to predict indicators such as machine overall equipment effectiveness (OEE) by utilising this data source [Thiede 2023]. Furthermore, approaches for segmenting the load profile offer the possibility of determining individual machine operations based on the load profile [Seevers 2019] or assigning the machining cycles of different manufacturing orders [Wächter 2023]. One obstacle to fully utilising the information potential of load profiles is the effort and expert knowledge required to interpret the data [Teiwes 2018].

This paper is intended to create a data basis for the development of automated approaches for the interpretation of load profile data. To this end, this paper describes various characteristics and value ranges that have been observed in the load profiles of machine tools. The evaluation and description include sections in which machining takes place on the machine. The examples presented are machines that can be categorised as milling, turning and grinding machines based on their main manufacturing technology. In terms of the degree of automation, all machines are classified according to [Hirsch 2022] as machining centres, which can perform other technologies in addition to the main production technology and have an automatic tool change and partially automatic workpiece change. The focus of the description in this paper is on load profiles with a time resolution of 1 sps (samples per second), as this appears to be suitable and widespread in practice. In addition, the effect of a reduced sampling rate on the load profile of machine tools is discussed and illustrated using the example of a rotary grinding machine.

2 BACKGROUND: LOAD PROFILES OF MACHINE TOOLS

The electrical load profile, hereinafter referred to simply as the load profile, refers to the electrical power drawn at the mains connection point of the machine.

A machine tool usually consists of different components that are supplied with electrical energy - for example feed and spindle drives, cooling systems, hydraulic and lubricant pumps, control units, etc. [Hirsch 2022]. The power drawn at the mains connection of the machine is the cumulation of the individual power demand of these components [ISO 14955-1].

Of the total electrical energy demand of a machine tool, the largest shares are accounted for by cooling, cutting fluid supply, the hydraulic unit and the drives [Denkena 2020]. However, the share of the total electrical energy demand does not allow any general conclusions to be drawn about the load characteristics of the respective components. The load characteristics of individual components can be described either as constant, e.g. for control units, cyclical, e.g. for cooling units, or variable, e.g. for the main spindle [Abele 2012]. Denkena et al. describe the load characteristics of spindles with a short peak peak at the start of an operation followed by an interval of constantly increased load [Denkena 2020]. As a result of rapid positioning operations and hereby acceleration of axis and spindles, short duration peak loads of high amplitudes occur. Deceleration of axis and spindles drives also leads to negative peak loads at the mains connection [Dietmair 2009]. The load behaviour of cooling units with 2-point control is described with a constantly increased base load and cyclically higher load blocks. The characteristics of high-pressure cooling lubricant pumps are also described with a base load and blocks of higher load, whereby the blocks are variable in size [Denkena 2020]. Eisele et al. show that the load behaviour of an investigated centrifugal pump can also exhibit short, smaller peak loads in addition to a base load if a higher volume flow is required from the machine for a short time [Eisele 2011].

In general terms, the load profile of machine tools is described in technical standards such as VDMA 34179 and ISO 14955-1. These differentiate between different energy modes – such as off, standby, ramp up, warm up, ready for operation, processing [ISO 14955-1, VDMA 34179]. These modes represent specific constellations of component activation: e.g. Standby may involve active control units and cooling circuits, while other systems remain off. As a result, different operating states are characterized by distinguishable electrical signatures in the load profile, as shown by findings in various studies [Dietrich 2020, Dehning 2019, Suwa 2016].

In this context, machining cycles can be interpreted as structured sequences of power pattern, that correspond to physical process stages. This is reflected in the work of Schraml, who identifies typical sequences consisting of spindle acceleration, cutting engagement and idle or transitional phases, each defined by characteristic load levels and temporal profiles [Schraml 2018]. Some preliminary work gives value ranges for the length in time or the observed mean power for the different sections. Suwa et al. report cutting times between 6 and 8 minutes for turning operations [Suwa 2016], while Dietrich et al. describe durations for machining cycles from 66 to 354 seconds [Dietrich 2020]. Schraml also describes durations of the individual sections ranging from a few seconds for e.g. spindle speed-up to several minutes for main cutting or idle phases [Schraml 2018].

Previous studies that process load profile data mostly rely on time series with a sampling rate of 1 sps (samples per second) or aggregation rates of 1 s, which has proven sufficient to distinguish energy states at the machine level [Liebl 2018, Teiwes 2018, Dietrich 2020, Dehning 2019]. High-frequency data is associated with higher costs for collecting and processing the data. Therefore, a compromise must be made when selecting the appropriate resolution of load profile data in an industrial context [Labbus 2019]. Accordingly, coarser resolutions, such as average values over 15-minute intervals, are also common at factory level [Dehning 2019, Walser 2021]. These are often based on billing purposes associated with the energy supply [Thiede 2012].

3 INFLUENCE OF SAMPLING RATE ON THE DETECTION OF PEAK LOADS

The appearance of load profiles in machine tools relies on the sampling rate of the measurement system. In this context, the number and magnitude of recorded load peaks are significantly influenced by the sampling rate. Initial measurements were conducted with a sensor system operating at a sampling rate of 10 sps, aggregated to 1 s, on the direct current (DC) side of the intermediate circuit of a tool machine. It was observed that both the number and the height of the recorded load peaks varied when the same machining program was recorded multiple times. This indicates that with a low sampling rate, peak loads may be represented differently from the real occurrence in the recorded time series.

In order to record the actual course of load peaks of machine tools, literature also suggests a minimum sampling rate of 40 sps since the peak loads have a duration of approximately 50 ms [Menz 2017]. To address this issue, in the scenario described above, additional sensors capable of sampling current and voltage at a rate of 500 sps were installed on the DC side of a machine tool. A comparison of load profiles recorded simultaneously with both, 10 sps aggregated with 1 s and 500 sps, showed that the higher sampling rate enabled the detection of more and higher load peaks (see Fig. 1).

The impact of varying the sampling rate was further examined by gradually reducing the sampling rate, starting at 500 sps. For the vertical grinding machining center under

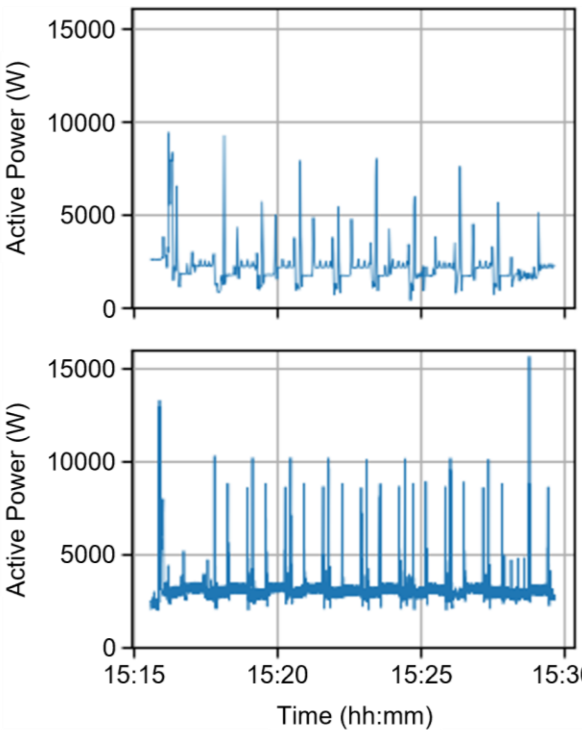

Fig. 1: Load curve of a machine tool during operation with 1 s (top) and 500 sps (bottom) aggregation/sampling rate

consideration a threshold was determined, at which load peaks start to diminish or disappear. The analysis revealed that peak load disappearance started to occur at approximately 170 sps, where the peak magnitudes first showed a reduction of less than 1%. More substantial losses, exceeding 10%, along with the complete disappearance of single peaks, were observed at sampling rates of 10 sps and below.

In industrial energy monitoring applications, temporal resolutions with aggregation periods of between 1 second and 15 minutes are common, although longer or shorter periods are occasionally found. Longer aggregation intervals of 1 h or more are more likely to be found when analysing the load profiles of entire buildings, whereas a aggregation period of 15 minutes is based on billing purposes. A data resolution of at least 0,1 sps is also recommended in the literature for analysing individual devices with dynamic clocking or load changes [Thiede 2012].

When analysing load profiles, taking into account the sampling rate, a distinction must be made between the sampling rate and the aggregation rate of the time series. The distinction concerns whether discrete sample values are present in the time series or whether several samples are aggregated to one value in the time series over an aggregation interval [Proakis 2007]. In this paper for clear differentiation the following definition is applied. The sampling rate is the frequency at which a continuous variable such as electrical power is sampled in discrete steps [Oppenheim 2013]. This is specified in samples per second (sps). Aggregated values are specified in the aggregation interval, e.g. in seconds. In commercially available data recorders for energy monitoring, electrical values are sampled at 26 ksps, for example [Emonio 2025]. The measured values are averaged over the set temporal measurement resolution, which corresponds to the aggregation rate, and saved as a time series value. In this example, with a temporal resolution of 0,1 s, each value of the load profile can be interpreted as the average of 2600 sampled values. Such downsampling has the effect of a moving average processing on the time series, so that load peaks appear as smoothed elevations. When interpreting aggregated data, it should be noted that the temporal resolution of the time series should already be understood as pre-filtering.

4 DESCRIPTION OF THE DATA SET

In order to provide an exemplary overview of the characteristic values found in the load profiles of metal-cutting machine tools, these are presented below.

4.1 Description of the machines considered

In the following description, nine machines are considered and each named with an identifier ID_M. These are listed in Tab. 1. The machines considered operate in an industrial application in machinery and equipment engineering, automotive industry, aerospace supply industry or research facilities. The machines are categorised by type according to their main manufacturing technologies milling (**M**), turning (**T**) and grinding (**G**). The milling and turning machines in question are machining centres that can perform other machining technologies in addition to the main technology and that have an automatic tool changer. Due to the degree of automation, the grinding machines are also classified as machining centres that can perform various grinding operations with automatic tool selection. All machines are operated with an NC-based control system.

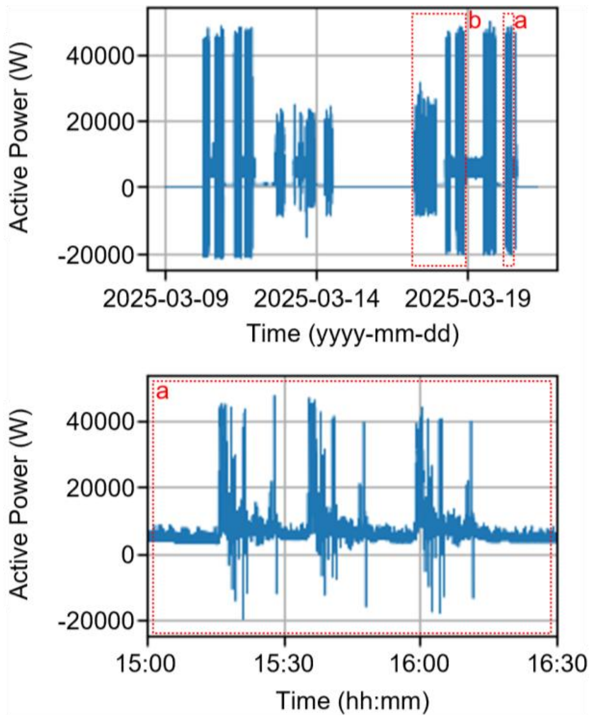

Fig. 2: Load profile of a turning machining centre over time with different machining cycles shown (top) and section with three identical pattern (bottom)

To categorise the energy dimension of the machines, their rated power P_N is listed on the nameplate.

4.2 Description and discussion of the data

As described above, the data was recorded using measuring devices with a sampling rate of 26'000 sps. The aggregation rate of the underlying time series is 1 s - consequently, each value of the time series is composed of an average of 26'000 samples.

The machines have several machine cycles in the period under consideration, that are either similar/identical or different. These appear in the load profile as repeating identical or different patterns (see Fig. 2 (bottom)). Identical patterns of one machine are summarised under one identifier ID_P. Fig. 2 (top) shows qualitatively how pattern differ, for example, in the level of their peak load (b). The number of pattern that are summarised under the same identifier is denoted by **n**. Consequently, the associated

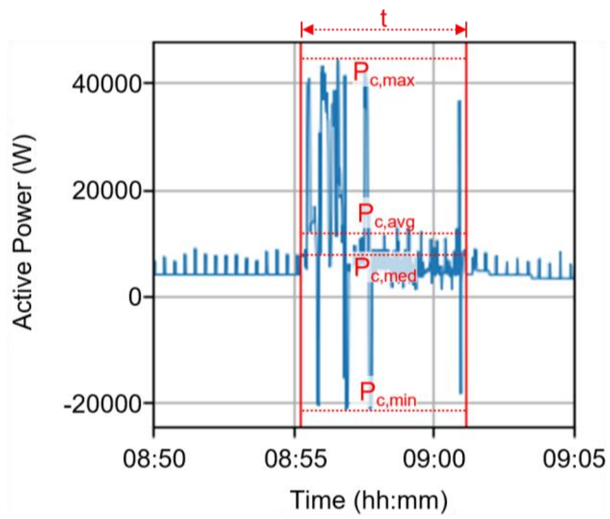

Fig. 3: Section of the load profile with one machining cycle and qualitative labelling of the characteristic values

Tab. 1: Value ranges and statistical values of the electrical load profile of metal-cutting machine tools during machining

ID_M	ID_P	Type	Industry	P_N	n	$t_{c,min}$	$t_{c,max}$	$t_{c,avg}$	$P_{c,min}$	$P_{c,max}$	$P_{c,avg}$	$P_{c,med}$	$P_{c,std}$	CV
1	1.1	M	Machinery	173	24	1100	1546	1184	-44101	88304	9164	8287	6838	0,75
1	1.2	M	Machinery	173	24	931	2193	1633	-13809	53064	9298	8485	3925	0,42
2	2.1	M	Machinery	113	36	1698	6863	4372	-37467	65304	8259	7628	2600	0,31
3	3.1	M	Machinery	160	44	577	1675	911	-15166	38846	6804	6623	2640	0,39
4	4.1	T	Machinery	65	60	328	406	337	-21824	48493	9925	6526	12637	1,27
4	4.2	T	Machinery	65	57	456	699	478	-8831	31533	5757	5257	1997	0,35
4	4.3	T	Machinery	65	50	756	912	777	-20737	49957	11184	7266	10628	0,95
5	5.1	T	Machinery	80	47	101	207	145	-4545	9507	2406	2649	1494	0,62
5	5.2	T	Machinery	80	357	90	217	95	-14634	21161	2138	2435	3050	1,43
6	6.1	T	Machinery	80	478	62	162	113	-6790	22395	7448	7046	3218	0,43
6	6.2	T	Machinery	80	67	170	239	214	-20599	42715	5890	5389	3560	0,60
6	6.3	T	Machinery	80	198	69	100	82	-8081	27361	6706	6572	4429	0,66
7	7.1	G	Machinery	53	14	392	701	469	5588	31993	15039	13701	4666	0,31
8	8.1	M	Machinery	104	18	883	1160	1088	-51733	94841	7730	6802	5661	0,73
8	8.2	M	Machinery	104	9	6573	10663	8343	-34122	71143	6892	6597	2285	0,33
8	8.3	M	Machinery	104	23	2390	4273	3426	-28213	63395	6897	6555	2621	0,38
9	9.1	G	Research	45	4	151	159	158	361	9192	2087	2017	850	0,41
9	9.2	G	Research	45	3	153	181	168	532	7239	2078	2115	763	0,37
10	10.1	T	Automotive	110	116	132	169	155	16696	70556	23253	21711	5573	0,24
10	10.2	T	Automotive	65	86	87	116	100	16809	65397	25072	23676	5118	0,20
11	11.1	G	Automotive	65	135	305	394	335	16560	33654	22877	23036	1800	0,08
11	11.2	G	Automotive	65	103	321	450	389	8648	29480	23131	23009	1727	0,07
12	12.1	G	Automotive	140	633	118	272	160	-38539	113593	24712	23782	10426	0,42
12	12.2	G	Automotive	140	471	73	233	142	-42076	108595	24803	23757	11246	0,45
12	12.3	G	Automotive	140	301	139	206	142	-19304	84067	24186	23153	8964	0,37
13	13.1	M	Aerospace	84	12	46714	48438	47790	-51727	107350	13522	13815	2790	0,21
13	13.2	M	Aerospace	84	4	72606	80342	77540	-52518	108453	13448	13635	4059	0,30
13	13.3	M	Aerospace	84	6	68982	73997	69902	-46664	96613	13186	13294	1901	0,14
14	14.1	T	Aerospace	82	2	15521	17263	16392	-44720	77242	13030	12443	3394	0,26
14	14.2	T	Aerospace	82	3	16641	34022	23081	-44692	77797	12899	11873	3307	0,26
15	15.1	G	Aerospace	58	2	58261	66320	62291	1736	19595	11461	11369	2919	0,25
16	16.1	M	Aerospace	58	2	32780	35614	34197	-29254	62222	6759	6675	2675	0,40
16	16.2	M	Aerospace	58	7	6097	20955	10360	-31988	66853	7426	6688	5286	0,71
17	17.1	G	Aerospace	200	2	3905	3941	3923	3181	22553	14376	13373	3698	0,26
17	17.2	G	Aerospace	200	2	1287	1418	1353	3184	22750	14051	14264	5371	0,38
17	17.3	G	Aerospace	200	3	3842	4337	4008	3195	24564	13916	13741	4238	0,30
17	17.4	G	Aerospace	200	3	1144	1196	1164	4073	22596	14090	12776	3762	0,27
18	18.1	T	Aerospace	65	24	2174	6910	3721	-18697	41146	5925	5232	2559	0,43
18	18.2	T	Aerospace	65	22	2148	9590	3794	-18347	39845	6307	5908	2577	0,41

statistical figures were determined from n samples. The statistical figures thus represent values for identical pattern. Different cycles are listed separately.

The length of a pattern, which represents the duration of the machining cycle, is indicated by t (see Fig. 3), where $\mathbf{t_{c,avg}}$ indicates the average, $\mathbf{t_{c,max}}$ the maximum and $\mathbf{t_{c,min}}$ the minimum duration under the identical patterns. The machining cycles of the machine tools analysed have a duration of between 62 s and 72'606 s (20 h 10 min 6 s).

For the power, values are also given for identical samples bundled together. $\mathbf{P_{c,avg}}$ is the average of the averaged power within identical patterns. $\mathbf{P_{c,max}}$ represents the maximum load peak that can be observed within the respective pattern. $\mathbf{P_{c,min}}$ represents the minimum value of the time series for the power demand within the respective segments. $\mathbf{P_{c,med}}$ is the average of the median values of the bundle of similar pattern. Due to high positive and negative peak loads as a result of power feedback, the observed values for the power range between -52,5 kW and 108,5 kW. The mean power values during processing ranges from 2,1 kW to 25,1 kW.

The load profiles of some machines show comparatively high standard deviations, which is characterised in a high coefficient of variation (**CV**). This seems to apply in particular to turning and milling machines, although there are also several machining cycles among these machines that have comparatively low and medium **CV** values.

Nomenclature

Shortcut	Unit	Description
CV	-	Coefficient of variation $\left(\frac{P_{c,std}}{P_{c,avg}}\right)$
ID_M	-	Machine identifier
ID_P	-	Pattern identifier
n	-	Number of pattern considered
$P_{c,avg}$	kW	Average power within identical pattern
$P_{c,max}$	kW	Maximum power within identical pattern
$P_{c,med}$	kW	Averaged Median of power values within identical pattern
$P_{c,min}$	kW	Minimum power value within identical pattern
$P_{c,std}$	kW	Averaged standard deviation of identical pattern
P_N	kVA	Rated power of the machine
$t_{c,avg}$	s	Average duration of identical pattern
t_{cmax}	s	Maximum duration of identical pattern
$t_{c,min}$	s	Minimum duration of identical pattern
Type	-	Machine type by main manufacturing technology
		M: Milling Machining Center
		T: Turning Machining Center
		G: Grinding Machining Center

One possible explanation is that turning and milling processes involve more frequent dynamic positioning operations with axis acceleration and deceleration, while grinding processes are less dynamic. This could result in different load behaviour with more or fewer single peak loads. However, it is not possible to make a general statement about the difference between turning, milling and grinding processes based on the **CV** during machining cycles.

Another factor could be the dimensioning of auxiliary units, such as chillers and fluid pumps, which have a rather constant or cyclical load behaviour with low dynamics. Auxiliary units with low dynamic load behaviour but comparatively high electrical power demand significantly increase the average power consumption, so that load peaks caused by axis movements may appear less significant in these cases.

5 SUMMARY AND OUTLOOK

The aim of this paper is to provide a basis for the development of automated approaches for analysing the load profiles of machine tools. Therefor an overview of electrical load profiles of machine tools during machining cycles is given. The value ranges for cycle times and power related figures are presented. It also shows how the time series of the electrical load profile is to be interpreted with regard to the sampling and aggregation rate.

The evaluation shows that there are significant differences between the load profiles of machine tools during machining cycles. This applies to the average power demand of the milling, turning and grinding machines examined, as well as other aspects. The duration of the machine cycles found ranges from a few minutes to several hours of processing time.

Further useful work in describing the characteristics of load profiles for cutting machine tools involve considering the influence of auxiliary units, feed and spindle drives, and their partial load profiles. In particular, it would be worth investigating whether generalisable statements about certain characteristics in the overall load profile can be related to the presence or relative dimensioning of individual components. Furthermore, expanding the scope of consideration to include additional machines and subdividing them according to their degree of automation would be a promising follow-up task.

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