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STATISTICAL EVALUATION OF IMPACT FACTORS TO THE ENERGY CONSUMPTION OF MACHINE TOOLS

In this paper, a method for the evaluation of the energy consumption of machine tools is presented. For this purpose, the energy consumption of various machine tools has been investigated experimentally. In order to increase the evaluation basis, measured values of energy consumption were also taken from literature. The evaluation contains an analysis of various factors concerning the productivity and the size of the investigated machine tools. This analysis is capable of detecting the impact factors to increase the energy-efficiency of production systems. It can further reduce the effort required for data acquisition when various machine tools are compared.

1. INTRODUCTION

In the last decades, the demand for consumer goods has been growing steadily, while the amount of available resources has decreased. As a result, there is a need for higher resource-efficiency. One of the most crucial resources is energy. The need for the energy-efficiency is even expressed in the directive of the European Commission 2009/125/EC “Ecodesign of Energy-related Products (ErP)” [1]. Considering the fact that the machine tools play an important role in production, increasing the energy-efficiency of machine tools significantly contributes to more efficiency in the production. Thus, the production needs processes, realized by energy-efficient machines. Machine tools (MTs) cause a substantial amount of the industrial energy consumption. Therefore, they will be focused by the Ecodesign of Energy-related Products (ErP) Directive 2009/125/EC [1] and have to become more energy-efficient [18]. Moreover, with rising energy prices energy-efficiency becomes generally more important in economics.

The aim of this paper is to investigate the dependence of the energy consumption of machine tools with regard to different technical parameters by using statistical analysis [2]. This investigation can reveal potentials for improvement of the energy-efficiency on the one hand, and, on the other hand, this investigation can set the basis for labels that enable

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a better comparison of machine tools regarding the energy consumption. This paper only focuses on machining centres for milling operations.

Recently, many machine tools have been investigated in terms of energy-efficiency. In order to generate a sufficiently large dataset for the statistical analysis, results of measurements of energy consumption of some machines that were conducted at the Institute for Machine Tools and Production Processes of the Chemnitz University of Technology are used in the dataset as well as measured results from literature [3-5]. The statistical analyses performed in this paper have two goals. The first goal consists in the reduction of the amount of technical parameters. For this reason, a principal component analysis is performed [6]. The second goal is to find out correlations and functions between the energy consumption and the other technical parameters. For doing this, correlation analysis and curve fitting are employed. The identified functions build a basis for the determination of energy labels for machine tools [2].

2. PREPARING THE DATASET

2.1. ENERGY CONSUMPTION

Electricity and compressed air are the main energy sources for machine tools. Electricity dominates the environmental impact of MTs at their entire life-cycle with a share of more than 90 % [7]. Therefore, this paper only considers electricity as energy source. Energy within material flows will be not regarded here [8].

Energy consumption is the cumulated power consumption in a defined period of time. Machine tools work in different operation modes [9-11]. Fig. 1 shows that the biggest share of the operation time of machine tools in a production line is taken up by time for waiting and moving operations without cutting [12],[13]. Moreover, many studies reveal that the majority of cutting processes do not increase the power consumption significantly [3-4],[8-9],[14]. Thus, for many cases the energy consumption of a machine tool can be evaluated approximately by the power consumption at the operation mode “ready for operation” in a time period plus the power consumption of the coolant system during an estimated cutting time. Therefore, the power consumption is used as an indicator for the energy consumption of a machine tool in this paper.

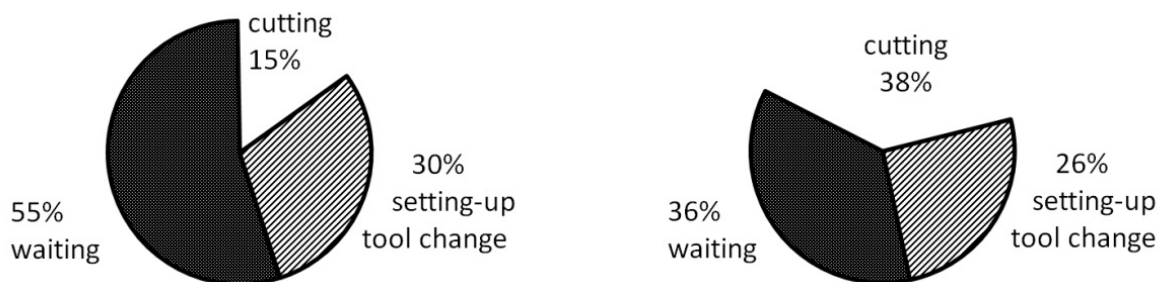


Fig. 1. Workload of cutting machine tools in batch and large-batch production [12],[13]

The electric power consumption for this dataset was measured with current sensor clamps and power analysers at the main power supply of the MT. Furthermore, published measuring results from literature were included to enlarge the dataset for the statistical analyses [3-5].

2.2. IMPACT FACTORES

The characteristic of a machine tool can be expressed by using many technical parameters that can be classified into the following groups:

a) General data (e.g. machine type, manufacturing processes, year of manufacture):

The machine type yield information about the possible realized manufacturing processes (e.g. turning or milling) and features (holes, pockets, 3-D-surfaces, etc.). Machines are comparable if they can realize the same type of machining processes [15], i. e. the machines are approximately of the same type. Furthermore, the year of manufacture can be linked up with the installed electric power, like shown in Fig. 2 on an example of the lathes installed at Volkswagen factories over 80 years [16]. The installed electric power has been rising steeply for the last decades. The significant increase of the installed electric power in the 1980s is related to the upcoming automation caused by the advance in computer technology.

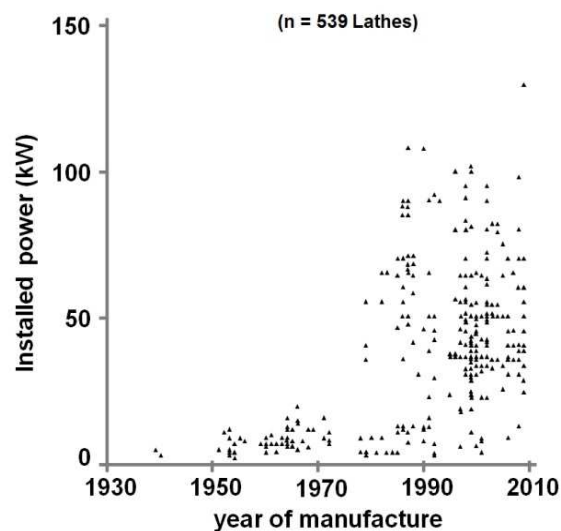


Fig. 2. Installed power of lathes in Volkswagen factories since 1930 [16]

b) Size (e.g. mass, dimensions of workpieces, machines):

Generally, the size of a MT corresponds to the maximum dimensions and the maximum mass of the workpiece. The space required for machining also needs to be considered. In literature [3], an approach to predict the energy consumption by using the work area is suggested. Thereby, the work area is defined by the length of the x and y axes for milling machines and by the length of x and z axes for

lathes. In literature [3], the work area is classified into three sizes: small ($A < 0.1 \text{ m}^2$), medium ($0.1 < A < 1 \text{ m}^2$) and large ($A > 1 \text{ m}^2$). Within each class, the energy consumption is expected to depend on the complexity of the MT, i.e. more complex MTs are expected to consume more energy.

The approach of classification was extended to 21 different MTs by own experimental measurements and values taken from other literature. Results of this approach are shown in Fig. 3. The power consumption in the operation mode "ready for operation" is taken as a measure. The MTs of the sample are sorted in ascending order of the energy consumption of each individual MT. It is obvious that the correlation to the work area is not distinct, though there is a general trend of larger MTs consuming more energy.

In the presented study the complexity is expressed by the number of servo axes. It is interesting to note that the number of servo axes does not increase continuously with the power consumption order. Therefore, the expected higher energy consumption of more complex MTs is not generally true for the given sample. Another measure is the mass of the MTs. Bongard et al. [12] detected a quadratic relation between the mass and the installed electric power for horizontal lathes.

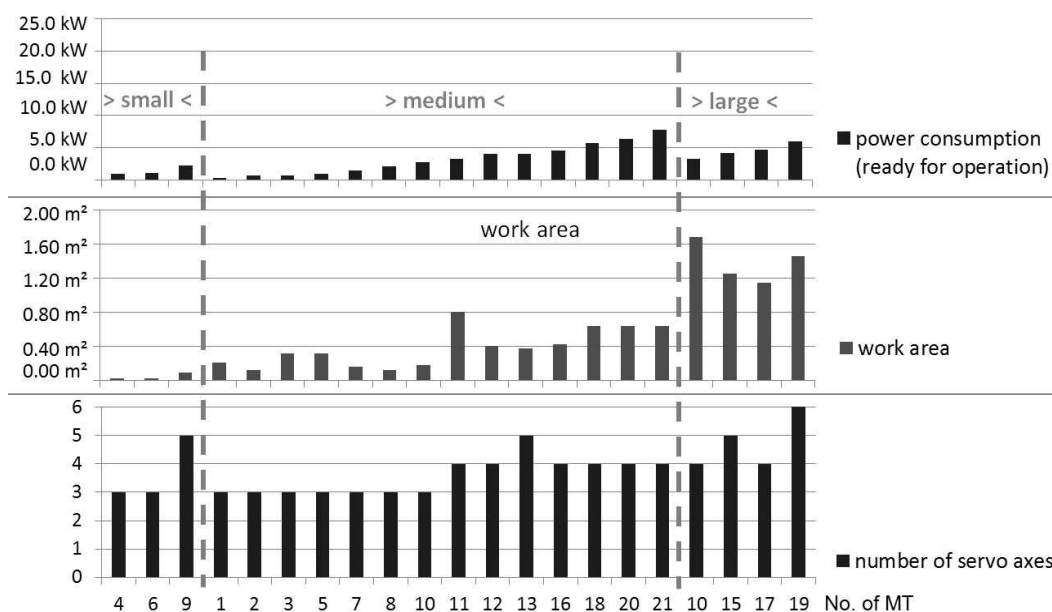


Fig. 3. Machine size categories and number of servo axes as impact factors to power consumption

- c) Productivity (e.g. speed, acceleration, power and torque of spindle and feed drives):

An important property of MTs is the productivity that can be expressed by speed, power and torque of the spindle, maximum feed rate and acceleration of the axes.

- d) Accuracy (e.g. positioning or machining accuracy):

The evaluation and comparison of the accuracy of MTs from datasheets is difficult, as there are many different standards applied. MT-manufacturers publish different

declarations regarding the accuracy, for instance positioning or machining accuracy. Furthermore, thermal stability is becoming more important for MTs aiming for high precision. In this paper, the positioning accuracy is considered as a comparable and available parameter influencing the energy consumption. Additionally, the positioning accuracy is combined with the arithmetic mean of linear axes travel to define a parameter that represents the relationship between the accuracy and the machine size.

- e) Auxiliary systems (e.g. coolant, air cleaning, cooling, lubrication, control):

Auxiliary systems work process-dependent (e.g. coolant, air cleaning) or process-independent (e.g. drive cooling, lubrication, control, light, hydraulic). Process-independent systems run most of the time, even when the machine is waiting. It is widely accepted that these systems inevitably cause a significant part in the measured power consumption in operation mode “ready for operation”. Process-dependent systems like coolant pumps account for a large portion of the energy consumed while machining. However, the contribution of the process-dependent systems can only be determined under certain conditions during a manufacturing process. Standards like the Japanese TS B 0024-1 [17] and the upcoming 14955-3 [1] might offer solutions for this problem.

In fact, the power consumption of coolant systems can differ in a wide range. This is due to the fact that high and low pressure pumps are often installed in the same machine. The energy consumption of these systems further depends on the tool used. For the reason of simplicity, this paper does not regard process-dependent auxiliary systems and machining operations.

- f) Environmental conditions (e.g. forms and quality of needed energy, climate in workshop):

Environmental conditions for MTs are difficult to describe by suitable values for an analysis of the energy consumption and are not going to be considered in the following analysis.

2.3. STATISTICAL DATASET

The dataset is represented by an m -by- p matrix \underline{X} of m observed objects (measured machine tools) and p parameters (potential impact factors) in the form of

$$\underline{X} = \begin{bmatrix} x_{11} & \cdots & x_{1p} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mp} \end{bmatrix} \quad (1)$$

The observed objects contain 21 machining centres which are capable of milling operations (18 milling and turn-mill machines and 3 mill-turn centres, [2-5]) Furthermore, the dataset provides 45 technical parameters including all allocable information from

machine documentations. From these 45 parameters 21 parameters are selected for further evaluation. The set of 21 parameters consists of the power consumption and 20 potential impact factors (see Table 1). The selection of the parameters was performed on the basis of the estimated impact, the comparability and the number of available values (more than 50 %) of each parameter within the sample of MTs.

Table 1. Technical parameters for the statistical analyses

Class	No.	Description
	0	electric power consumption in operation mode “ready for operation” [kW]
a)	1	number of servo axes
	2	installed electrical power [kVA]
b)	3	maximum work piece mass [kg]
	4	machine mass [kg]
	5	arithmetic mean of table size [mm]
	6	table area [m ²]
	7	linear axis travel x [mm]
	8	linear axis travel y [mm]
	9	linear axis travel z [mm]
	10	work area of linear axis x-y (milling) or x-z (mill-turn) [m ²]
	11	work volume of linear axis x-y-z [m ³]
c)	12	arithmetic mean of maximum feed rate (m·min ⁻¹)
	13	arithmetic mean of maximum acceleration in linear axes x-y-z [m·s ⁻²]
	14	maximum tool mass [kg]
	15	maximum spindle power 100% ED [kW]
	16	maximum spindle torque 100% ED [Nm]
	17	nominal spindle speed [min ⁻¹]
	18	maximum spindle speed [min ⁻¹]
d)	19	position accuracy [μm]
	20	arithmetic mean of linear axes travel / position accuracy [mm·μm ⁻¹]

As a result, a 21-by-21 matrix for statistical analysing is achieved. In this matrix, there are some empty cells represented by NaN (Not a Number). The NaN-values arise due to the missed information from the literature. Some statistical methods are not able to work (ignore) with NaN-values. In order to overcome this fact, the NaN-values were substituted in two ways, either using mean values of the existing set of data or by “expert” estimations.

3. STATISTICAL EVALUATION

In this chapter, a method for the evaluation of the energy consumption of machine tools is presented. It contains three tools of statistical analysing which are carried out with

the dataset of machine parameters. In order to get an overview about the correlation between impact factors and the power consumption, corresponding correlation coefficients are computed as the first step. In a second step, the Principal Component Analysis (PCA) can show the parameters with significant impact on a dataset. This can help to reduce the number of parameters and thus the effort required for data acquisition and evaluation. In the last step, curve-fitting is performed to obtain a mathematical function between the impact factors and the power consumption. This can allow normalizing power consumption in order to compare different MTs.

3.1. CORELLATION ANALYSIS

The empiric correlation coefficient R describes the linear relationship between data x and y by the following equation:

$$R = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2 \cdot \sum_{i=1}^n (y_i - \bar{y})^2}} = \frac{Covar_{xy}}{\sqrt{Var_x \cdot Var_y}} \quad (2)$$

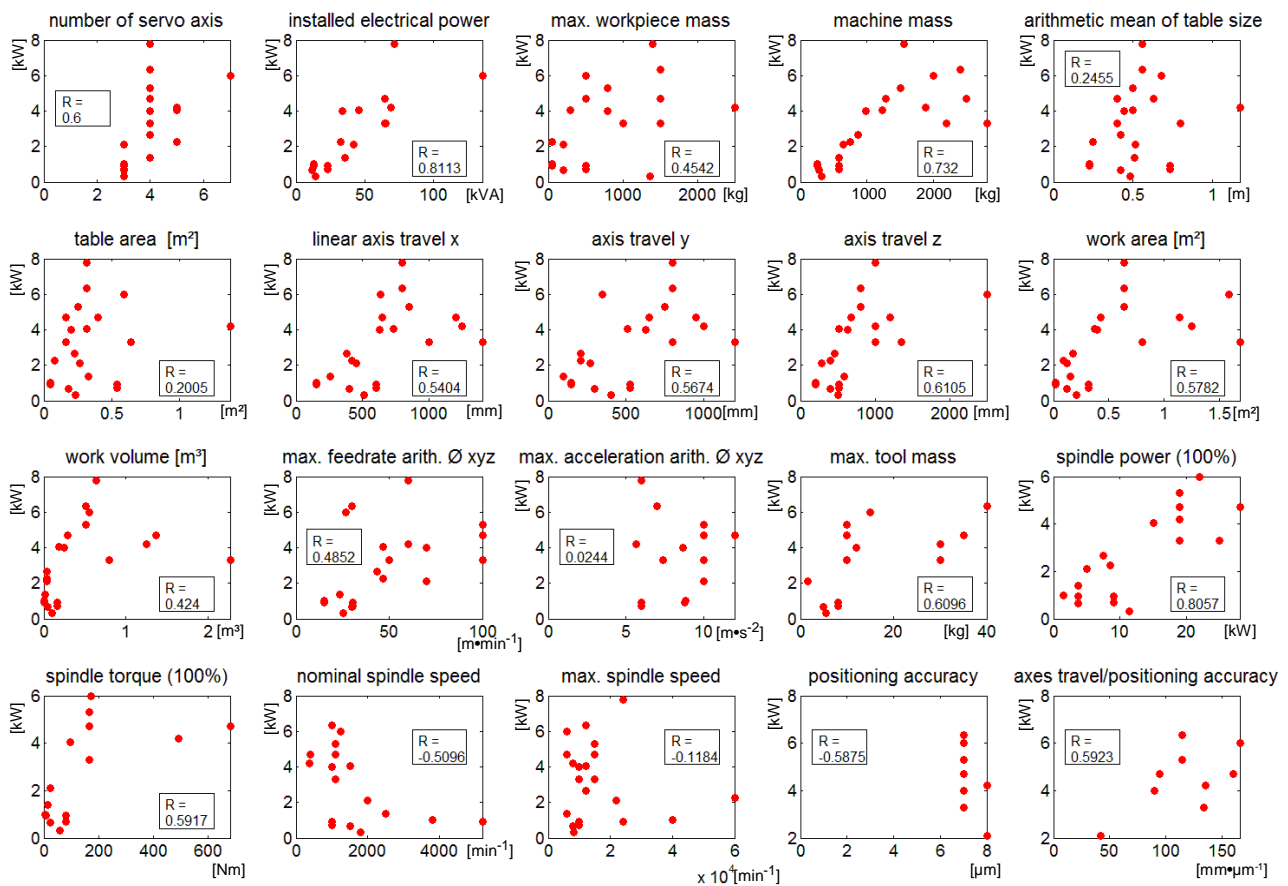


Fig. 4. Scatter plots of 20 impact factors (abscissas) with power consumption (ordinates) and correlation coefficients

The range is $-1 < R < 1$ where -1 means “perfect” linear negative dependence, 1 “perfect” linear positive dependence and 0 no linear dependence. The results of 20 correlation analysis are depicted in Fig. 4. In this scatter plot, each abscissa and every ordinate represent a selected impact factor and the power consumption, respectively. The numbers of the parameters correspond to the numbers in Table 1. This visualization allows a better understanding of the calculated correlation coefficients. Moreover, a non-linear relation can be recognized. Based on this, some impact factors are selected for the curve-fitting.

The evaluation shows the highest correlation coefficient $R = 0.811$ for the impact factor number 2 (installed electrical power) with regard to the power consumption. The second largest correlation coefficient $R = 0.805$ is found for parameter 15 (maximum spindle power 100% ED). That is, the installed electric power and the maximum spindle power can be expected to have the biggest impact on the energy consumption of a MT.

3.2. PRINCIPAL COMPONENT ANALYSIS

Principal Component Analysis (PCA) is a tool of the multivariate statistics and describes linear relations between parameters in a dataset assuming a normal (Gaussian) distribution of the parameters. The idea of PCA consists in the fact that data are a cloud of points in a p -dimensional space and the line with the best approximation for those points is the first “principle component”. It could be imagined like transforming the first axis of the p -dimensional space into the direction with the largest variance. The second axis (second principal component) stands orthogonal to the first one and have the second largest variance, and so on. The number of components is equal to the number of parameters. For performing the PCA, a p -by- p covariance matrix is defined. The values of each row vector in this matrix have to be centered regarding the mean value of the corresponding row vector. Furthermore, the values of each parameter were normalized to its arithmetic mean as the large-scale differences between parameters would falsify the PCA results (e.g. the parameter regarding the acceleration contain values in range from 5 to $14 \text{ m}\cdot\text{s}^{-2}$ and the parameter spindle speed is in range of 5000 to 60000 min^{-1}). The PCA cannot calculate with NaN-values, which are present in the original dataset. As mentioned above, the NaN-values were replaced either by arithmetic mean values or by “expert estimations”. Subsequently, the PCA computes the covariance matrix from the matrix X . In the results of both PCA in form of the eigenvalues of the covariance matrix are assorted. The eigenvalues express the parts of a component in the total variance of the dataset. The variance-vectors (VarVect and VarVectCumul) show this in relative and cumulative way. Only 7 components represent approximately 95% of the total variance of the dataset. This implies that only 7 components should be considered in the next investigation (depicted by the bold lines) at which the other components can be neglected.

Table 3 comprehends the matrix of coefficients of the first 7 components for the matrix with mean values as well as with expert-estimations. The values in the first column imply the contribution of the corresponding parameter to the first principal component; the second column corresponds to the second principal component, and so on. If the matrix with mean values is used, it is obvious that the contribution of the parameter 19 (position

Table 2. Eigenvalues of the covariance-matrix

No. of Comp.	dataset with arithmetic mean values			dataset with estimated values		
	Eigenvalue	VarVect	VarVectCumul	Eigenvalue	VarVect	VarVectCumul
1	6.09	60.67 %	60.67 %	7.24	60.97 %	60.97 %
2	0.88	8.77 %	69.44 %	1.22	10.26 %	71.24 %
3	0.81	8.08 %	77.52 %	0.99	8.32 %	79.56 %
4	0.70	7.01 %	84.53 %	0.78	6.55 %	86.11 %
5	0.51	5.03 %	89.56 %	0.60	5.09 %	91.20 %
6	0.34	3.38 %	92.94 %	0.39	3.24 %	94.45 %
7	0.31	3.12 %	96.07 %	0.24	2.04 %	96.49 %
8	0.15	1.48 %	97.55 %	0.16	1.37 %	97.86 %
9	0.10	1.00 %	98.55 %	0.08	0.63 %	98.49 %
10	0.05	0.54 %	99.08 %	0.06	0.50 %	99.00 %
11	0.04	0.35 %	99.44 %	0.05	0.43 %	99.42 %
12	0.02	0.18 %	99.62 %	0.03	0.21 %	99.64 %
13	0.01	0.14 %	99.76 %	0.02	0.15 %	99.79 %
14	0.01	0.09 %	99.86 %	0.01	0.10 %	99.89 %
15	0.01	0.06 %	99.92 %	0.01	0.06 %	99.94 %
16	0.00	0.04 %	99.97 %	0.00	0.03 %	99.97 %
17	0.00	0.02 %	99.99 %	0.00	0.02 %	99.99 %
18	0.00	0.01 %	100.00 %	0.00	0.01 %	100.00 %
19	0.00	0.00 %	100.00 %	0.00	0.00 %	100.00 %
20	0.00	0.00 %	100.00 %	0.00	0.00 %	100.00 %
21	0.00	0.00 %	100.00 %	0.00	0.00 %	100.00 %

accuracy) is negligible. A similar statement can be made for parameters 1 (number of servo axes), 13 (arithmetic mean of maximum acceleration in linear axes x-y-z) and 20 (arithmetic mean of linear axes travel / position accuracy). This further implies that these parameters are irrelevant for the statistical investigation. On the other hand, the largest contribution to the first component makes parameter 11 (work volume) followed by the parameters 10 (work area) and 16 (maximum spindle torque). Additionally, the parameter 16 and parameter 6 have the most significant impact on the second and third component.

If the matrix with expert estimations is analysed, the contribution made by parameters 1, 13, and 19 is negligible. In contrast, the parameters 10, 11, and 16 contribute to the principal components significantly. In conclusion, it can be said that parameters 1, 19, and 20 do not have to be regarded in the further analysis. The coefficients of the parameters over the components scatter in a wide range. For this reason, it is not possible to make a cluster of many parameters in order to reduce their number. Only the above mentioned parameters can be neglected, i.e. parameters 1, 13, 19, and 20. The scatter plots for these parameters (see Fig. 4) confirm this finding despite the corresponding correlation coefficients. It is surprising that the parameter concerning accelerations (No.13) does not play an important role. In this case, the arithmetic mean of accelerations in all linear axes is not adequate. It

Table 3. Machine parameters and first 10 components of the PCA matrix

Component	mean value							expert-estimation						
	1	2	3	4	5	6	7	1	2	3	4	5	6	7
P0 power consumption	0.170	-0.345	-0.091	-0.234	0.117	0.324	-0.444	0.158	0.189	-0.252	0.245	0.343	-0.047	0.280
P1 number of servo axes	0.049	-0.094	-0.116	-0.067	0.169	-0.027	0.011	0.039	0.070	0.012	0.178	0.036	0.146	0.017
P2 installed electrical power	0.166	-0.241	-0.400	-0.146	0.193	-0.079	-0.063	0.166	0.127	-0.083	0.427	0.031	0.194	0.193
P3 max. work piece mass	0.256	0.291	0.162	0.003	0.047	0.295	-0.366	0.266	-0.117	0.194	-0.322	0.650	0.001	-0.057
P4 machine mass	0.248	-0.209	-0.021	0.037	-0.070	0.172	-0.101	0.229	0.164	-0.097	0.065	-0.001	-0.101	-0.082
P5 arith. mean of table size	0.120	0.249	-0.072	-0.018	0.079	-0.141	-0.109	0.108	-0.158	0.171	0.010	0.066	0.127	0.117
P6 table area	0.235	0.508	-0.132	0.018	0.374	-0.352	-0.174	0.207	-0.272	0.440	0.019	0.148	0.463	0.237
P7 linear axis travel x	0.198	0.007	0.076	0.016	-0.154	-0.107	-0.115	0.183	0.026	0.019	-0.107	-0.027	-0.055	0.132
P8 linear axis travel y	0.208	0.006	0.121	0.038	-0.247	-0.019	-0.254	0.197	0.019	-0.020	-0.182	0.065	-0.195	0.153
P9 linear axis travel z	0.208	-0.177	-0.420	-0.067	0.150	0.007	0.211	0.188	0.077	0.016	0.483	-0.013	0.119	-0.212
P10 work area	0.358	-0.097	-0.296	0.138	0.045	-0.103	0.159	0.325	0.095	0.168	0.301	-0.093	-0.001	-0.094
P11 work volume	0.484	-0.054	0.111	0.557	-0.293	-0.160	0.090	0.439	0.211	0.325	-0.179	-0.312	-0.427	-0.014
P12 arith. mean of max. feed rate	0.107	-0.228	0.220	-0.311	-0.335	-0.205	-0.042	0.102	0.100	-0.314	-0.145	-0.142	0.053	0.614
P13 arith. mean of max. acceleration	-0.013	-0.112	0.030	-0.062	-0.104	0.004	0.136	-0.013	0.055	-0.115	-0.018	-0.014	-0.083	0.232
P14 max. tool mass	0.172	-0.030	0.204	0.219	0.304	0.501	-0.026	0.301	-0.003	0.141	-0.074	-0.259	0.039	0.092
P15 max. spindle power (ED 100%)	0.216	-0.152	-0.014	-0.105	-0.138	-0.061	0.146	0.200	0.145	-0.290	0.005	0.414	-0.231	-0.269
P16 max. spindle torque (ED 100%)	0.342	0.011	0.522	-0.367	0.341	0.000	0.480	0.342	0.091	-0.421	-0.378	-0.200	0.576	-0.345
P17 nominal spindle speed	-0.171	-0.095	-0.031	0.462	0.123	0.245	0.262	-0.226	0.593	0.340	-0.062	0.041	0.163	-0.163
P18 max. spindle speed	-0.144	-0.473	0.329	0.272	0.441	-0.467	-0.298	-0.148	0.575	0.125	-0.177	0.140	0.188	0.226
P19 position accuracy	0.000	0.019	0.005	0.005	0.015	-0.027	-0.015	0.015	-0.094	-0.013	0.001	0.005	-0.020	0.029
P20 axes travel / position accuracy	0.041	-0.008	-0.028	0.000	0.106	0.057	0.162	0.178	0.102	0.001	0.109	-0.008	-0.039	-0.011

would be reasonable to make such parameter by using the maximum value or product of the values. This can be seen on the example of parameter 5 (arithmetic mean of table size) and 6 (table area). While the parameter 6 is strongly distinct, the variance of the parameter 5 is reduced by the calculation of the arithmetic mean. Furthermore, the contribution of the power consumption is not as significant as some other parameters though its variance cannot be neglected.

3.3. CURVE-FITTING AND COEFFICIENT OF DETERMINATION

In order to obtain a mathematical description for the dependence of the power consumption on the other parameters the curve-fitting is performed in this chapter. Additionally, the coefficient of determination (R^2) is simultaneously evaluated to assess the quality of the mathematical function regarding the real parameter values.

Based on the facts resulting from the PCA, the correlation coefficients and the scatter plots (see Fig. 4) the parameters 2, 4, 9, 10, 14, 15, 16, and 17 (see Table 4) are selected for the curve-fitting.

The mathematical functions that parameter are estimated by the curve-fitting are chosen so that the trends in the scatter plots can be reproduced. In order to reproduce the trends in the scatter plots the following mathematical functions are chosen:

1. Linear function in the form: $y = ax + b$
2. Exponential function in the form: $y = a \exp^{bx} + c \exp^{dx}$

3. Quadratic polynomial function in the form: $y = ax^2 + bx + c$

4. Power function in the form: $y = ax^b + c$

The coefficients of these functions estimated by the curve-fitting are assorted including the coefficients of determination R^2 in Table 4.

Table 4. Values for the variables of the curve-fitting functions including coefficients of determination

curve-fitting type		linear functions			exponential functions				
variable		a	b	R ²	a	b	c	d	R ²
P2	installed electrical power	5.42E-02	3.80E-01	0.658	-	-	-	-	-
P4	machine mass	1.93E-04	8.40E-01	0.536	-	-	-	-	-
P9	linear axis travel z	2.56E-03	1.28E+00	0.373	-	-	-	-	-
P10	work area	2.48E+00	1.86E+00	0.334	2.74E+04	-9.70E-01	2.74E+04	-9.70E-01	0.564
P14	max. tool mass	1.00E-01	1.74E+00	0.372	1.23E+00	5.50E-02	-	-	0.000
P15	max. spindle power (100%)	1.80E-01	4.30E-01	0.649	5.75E+00	-4.79E-04	-	-	0.590
P16	max. spindle torque (100%)	6.13E-03	1.77E+00	0.350	-	-	-	-	-
P17	nominal spindle speed	8.60E-04	4.38E+00	0.260	-	-	-	-	0.305

curve-fitting type		quadratic functions				power functions			
variable		a	b	c	R ²	a	b	c	R ²
P2	installed electrical power	4.33E-04	1.10E-01	-8.70E-01	0.742	2.45E+00	3.20E-01	-5.05E+00	0.718
P4	machine mass	-	-	-	-	-5.58E+01	-8.40E-02	2.92E+01	0.655
P9	linear axis travel z	-	-	-	-	-1.61E+03	-1.50E-03	1.60E+03	0.473
P10	work area	-	-	-	-	8.21E+00	1.90E-01	-3.56E+00	0.459
P14	max. tool mass	-4.69E-03	3.00E-01	5.10E-01	0.428	2.39E+00	3.00E-01	-1.82E+00	0.416
P15	max. spindle power (100%)	-2.20E-03	2.40E-01	1.40E-01	0.654	2.10E-01	9.50E-01	3.40E-01	0.649
P16	max. spindle torque (100%)	-	-	-	-	1.78E+00	2.20E-01	-1.98E+00	0.523
P17	nominal spindle speed	-	-	-	-	-7.00E-01	2.90E-01	8.65E+00	0.292

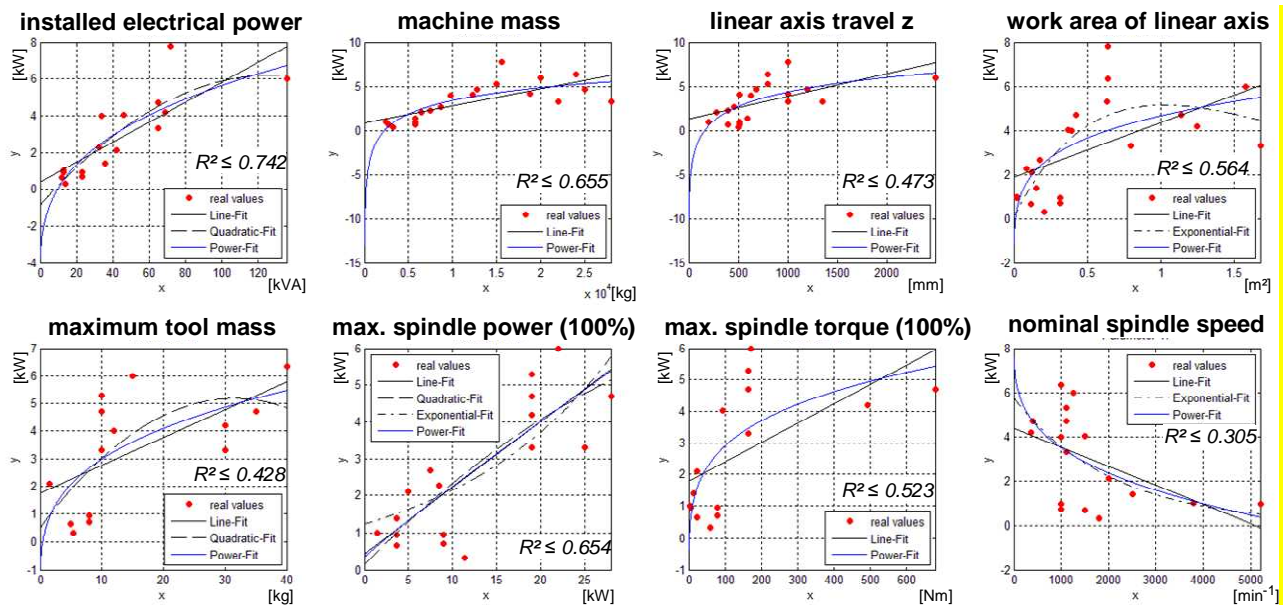


Fig. 5. Curve-fit of selected parameters and power consumption

If the coefficients of determination are evaluated it can be said that the dependences of the power consumption on the parameters 2, 4, 10, 15, and 16 are approximated best way by the quadratic polynomial function, the power function, the exponential function, the quadratic polynomial function and the power function, respectively. For the other parameters a mathematical expression does not seem to be very reasonable due to the coefficients of determination lower than 0.5. Fig. 5 depicts the plots of the real values and corresponding fitted functions. This figure implies that especially installed electric power (parameter 2), machine mass (parameter 4) and the maximal spindle power (parameter 15) can be recommended for the estimation of the power consumption of machining centres for milling operations under using the fitted functions. If the labeling of machine tools is addressed, the most appropriate parameters are the installed electric power (parameter 2) and the maximal spindle power (parameter 15). These two parameters can be normalized by the coefficients from the Table 4 with a sufficient accuracy in a simple way.

4. CONCLUSION

In this paper a methodology for the statistical evaluation of the energy consumption of machine tools is presented. Especially, the dependences of the energy consumption on various technical parameters of a machine tool are addressed whereby machining centres for milling operations are regarded. The power consumption in the operation mode “ready for operation” is used as the indicator for the overall energy consumption. The dataset is represented by an m -by- p matrix of m observed objects (measured machine tools) and p parameters (potential impact factors). A correlation analysis between 20 impact factors and the power consumption is carried out. Moreover, the Principal Component Analysis (PCA) is performed to find out parameters with significant impact on a dataset which allows reducing the number of parameters. Finally, curve-fitting is applied to derive mathematical functions between the impact factors and the power consumption. By use of this methodology, the number of parameters is reduced. Only five parameters feature a relation to the power consumption that can be described mathematically with sufficient accuracy. From these five parameters, three parameters should be used for the estimation of the power consumption of machining centres for milling operations. Furthermore, two parameters are suitable for normalizing the power consumption. The normalizing is enormously important for the intended labeling of MTs due to the diversity of their technical parameters.

The future work will focus on the enlargement of the dataset. Furthermore, supplemental parameters are investigated in order to represent the features of machine tools in an appropriate way.

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