Key performance indicators for assessing inherent energy performance of machine tools in industries

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Key performance indicators for assessing inherent energy performance of machine tools in industries

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Increasing attention has been paid toward enhancing energy retrofitting in machine tools due to its enormous energy consumption and high energy-saving potential. Developing energy-efficient machine tools and selecting appropriate machine tools in procurement processes are two effective approaches for saving energy. However, existing studies on the evaluation of energy performance to support the design and selection of machine tools, rarely consider various process controls, which have considerable impact on the energy performance of machine tools. This study proposes a group of key performance indicators, which are referred to as 'inherent energy performance' (IEP) indexes, to support the design and selection of machine tools with the consideration of the main process controls in the usage phase and their interaction. A systematic method is introduced to acquire the IEP indexes. The method involves a simplified measurement of basic data and the calculation of the indexes from the data. A case study indicates that the proposed indicators succeed in obtaining the energy demand information of almost all machine system activities and can be used to provide basic data for developing energy information labels, selecting matching machine tools, and designing energy-efficient machine tools.

Keywords: energy index; machine tools; inherent energy performance; energy management; energy efficiency manufacturing

1. Introduction

Continuously increasing energy demands and strict energy-related greenhouse gas emission directives have led the manufacturing industry to pay more attention to saving energy (Prabhu, Trentesaux, and Taisch 2015; Liu et al. 2017). The energy retrofitting of machine tools has become a valid method for reducing energy consumption and greenhouse gas emissions (Su et al. 2017), and its political and scientific importance is increasing worldwide. The ISO standardisation body (ISO/TC39 WG 12) initiated the ISO 14995 series to measure the energy consumption of machine tools (ISO 2016). The European Commission launched a series of eco-design directives, 2009/125/EC (European Union 2012). Similar initiatives have been undertaken in China (Cai et al. 2017), Korea (Lee, Woo, and Roh 2017), and Australia (Tolio et al. 2017). Among energy-saving strategies, developing energy-efficient machine tools and selecting appropriate machine tools in procurement processes are two effective approaches for the energy saving of machine tools as active time may continue throughout the usage phase of a machine tool (Zhou et al. 2015).

Evaluating the energy performance of machine tools is a precondition for developing energy-efficient machine tools (Neugebauer et al. 2011) and selecting matching machine tools in procurement processes (Liu et al. 2018). Scholars and organisations have conducted numerous studies on the energy performance evaluation of machine tools. For example, the ISO standardisation body initiated the ISO 14995 series to implement the environmental evaluation of machine tools, considering the energy performance of relevant function(s) or machine components as evaluation parameters for design procedures (ISO 2014). Schudeleit et al. (2016) developed a metric to quantify the energy efficiency of machine tool design for the standardised evaluation of machine tools by considering the efficiency of machine components. In addition to reference component methods, a few approaches based on a reference part have been employed to assess the energy performance of machine tools. A test part that involved face milling, drilling, pocketing, and slotting was designed by Bhinge et al. (2015) to generate energy data for simulating and evaluating the energy demands of machine tools. In their study, the test part and the comparison of energy performance are limited to machine tools with similar specifications. To compare different types of machine tools, Behrendt, Zein, and Min (2012) presented a detailed test procedure based on standardised parts to monitor and

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evaluate the energy performance of machine tools. Furthermore, regarding evaluation to support purchasing machine tools, Cagdac Arslan, Catay, and Budak (2004) developed a decision support system to select suitable machine tools for developing a new manufacturing system, considering spindle speed and power as evaluation indexes. A series of multi-objective decision-making algorithms, such as the fuzzy AHP and ANN (Taha and Rostam 2011), a hybrid of fuzzy AHP and PROMETHEE (Taha and Rostam 2012), and an integration of fuzzy AHP and GRA (Samvedi, Jain, and Chan 2012), were employed to evaluate the energy performance of machine tools for selecting machine tools in procurement processes.

The energy performance indexes employed to assess the energy performance of machine tools in the aforementioned studies are typically mainly based on the power demand of machine components, such as motor power and spindle power, or on the specific energy performance during a machining process, e.g. the specific energy consumption for a reference workpiece. In fact, the energy performance of machine tools is determined by the intrinsic characteristics and various process controls of its users (Asrai, Newman, and Nassehi 2018; Diaz, Redelsheimer, and Dornfeld 2011). The studies conducted by Kara and Li (2011) and Luan et al. (2018) indicated that process controls have considerable effect on the energy demand or performance of machine tools. For example, the power demand in the standby state of machine tools depends on the on/off state of auxiliary equipment (Li et al. 2011). The idling power of machine tools is closely related to spindle revolving speed (Liu, Liu, and Qiu 2017). These non-negligible influences of process controls on the energy consumption of machine tools imply that the aforementioned component or process indexes are insufficient for assessing the energy performance of machine tools because various process controls in the usage phase (e.g. probability distribution of spindle revolving speed) are not considered in the indexes.

This study proposes an index system to assess the energy performance of machine tools by considering various process controls in the usage phase and their influences. The proposed indexes, which are also referred to as inherent energy performance (IEP) indexes, could provide a quantitative evaluation method for developing energy-efficient machine tools and selecting matching machine tools in procurement processes. Moreover, a systematic method is introduced for acquiring the proposed indexes. The proposed indexes provide the following two advantages compared with the existing indexes: the effects of various process control distributions in the usage phase (e.g. probability of spindle revolving speeds) are considered, and the detailed energy demand for any specific machine tool activity is included.

The rest of this paper is structured as follows: Section 2 describes the goal and scope of the study. Sections 3 and 4 present the specific indexes for assessing the IEP of machine tools and the systematic method for acquiring the indexes, respectively. Section 5 describes a case study and the potential application of the proposed indexes.

2. Goal and scope definition

The energy consumption in a machining process typically consists of the energy derived from the intrinsic functions of machine tools, such as movement, rotation, and machine cooling, and the energy required by a tool tip to remove workpiece material (Gutowski, Dahmus, and Thiriez 2006). In a broad sense, the energy performance related to the intrinsic characteristics or functions is referred to as the IEP of machine tools and the energy performance of removing workpiece material is referred to as process energy performance, as presented in Figure 1.

The objective of the study is to assess the IEP of machine tools, including assessment indexes and the method for acquiring the indexes, based on the following three aspects: First, the influence of IEP on the energy consumption of machine tools continues throughout the usage phase, and not just a single process (Tuo et al. 2017). Second, IEP is unique for each machine tool because the structures and corresponding components are fixed. This prevents disputes caused by the different test results of various test pasts (Tuo et al. 2018). Furthermore, the energy-consumption characteristics of components, such as the power demand of spindles, feed power, and auxiliary power, are included in the IEP of machine tools. As a consequence, the IEP of machine tools can also provide data for their retrofitting.

3. Indexes for assessing the IEP of machine tools

3.1. *Decomposition of the IEP of machine tools*

Decomposing the IEP of machine tools is a valid method for studying the IEP characteristics of machine tools and developing an index system to assess the IEP of machine tools. We consider a milling machine as an example to illustrate the decomposition in detail. The IEP in one machining process is decomposed into the following five parts: standby power, starting energy, idling power, feed power, and additional loading loss power, as shown in Figure 1. Standby power refers to the power demand of the procedure from the switching on of the main power switch to starting the spindle. Its value generally depends on the on/off state of peripheral components such as hydraulic systems, cooling systems, and lighting systems. Starting energy is the energy consumption of the procedure from zero rpm to the required rpm of the spindle. Idling power is the

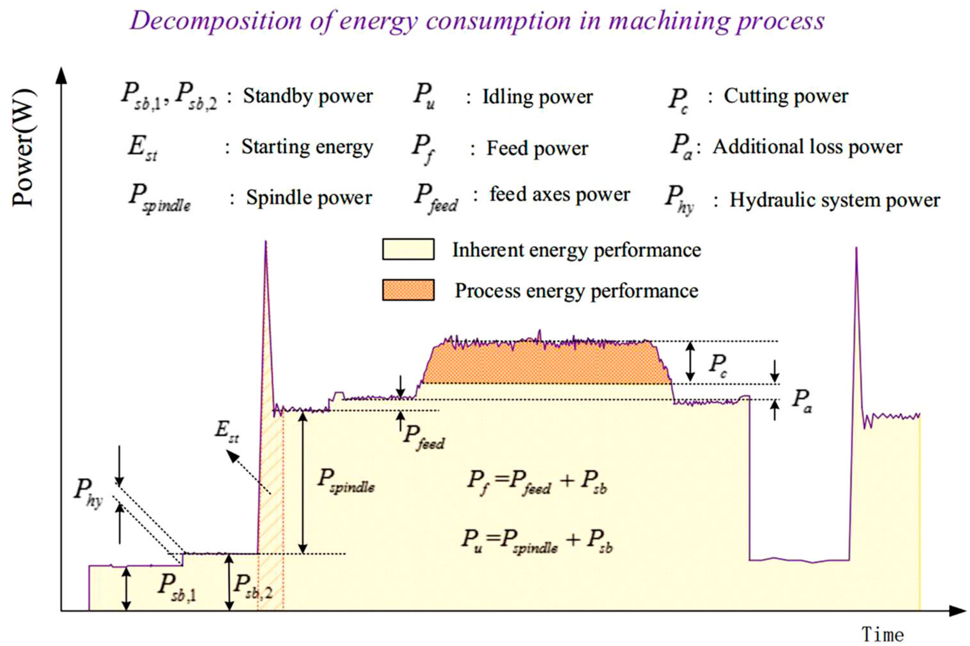

Figure 1. Decomposition of energy consumption in machining process.

power demand when the spindle is running without load. It is typically expressed as the summation of spindle power and standby power. Feed power is the power demand when the spindle is off but the feed axes are running without load after standby. It is generally expressed as the summation of the corresponding feed axes power and standby power, as shown in Figure 1. Additional loading loss power refers to the loss generated by the load of the spindle system in the cutting process. In most cases, starting energy (Lv et al. 2017), idling power (Tuo et al. 2018), and additional loading loss power (Xie, Liu, and Qiu 2016) are determined by spindle revolving speed while feed power depends on feed rate.

3.2. *IEP indexes of machine tools*

Based on the decomposition of IEP, a series of indicators are proposed to assess the IEP of machine tools, with the consideration of the effects and distributions of process controls in the usage phase. The proposed indexes address the energy consumption of a machine tool at two different levels, namely, the detailed data for any specific machine tool activity and the comprehensive mean energy consumption under various process controls. The former is expressed by energy-consumption function indexes and describes the energy demand at any machine tool activity. For the latter, equivalent energy-consumption indexes are proposed to represent the comprehensive mean energy demand of a machine tool under the same operational state. This is helpful for ordinary consumers, who are typically concerned about general energy consumption. Table 1 summarises the type, symbol, and other information of the proposed indexes.

By analysing the energy composition shown in Figure 1 and the energy-consumption function indexes described in Table 1, it can be inferred that the energy demand of machine tools at any status or process can be estimated using the proposed consumption function indexes. Namely, the proposed indexes include all IEP characteristics of machine tools. Therein, the loading loss coefficient function is used to compute additional loading loss power because the loading loss coefficient is generally expressed as the ratio of additional loading loss power P_a to cutting power P_c (Tuo et al. 2017). In addition, various process controls in the usage phase are considered by introducing the main factors that influence energy consumption and their distribution. For example, equivalent idling power represents the influence of various spindle controls on the energy consumption of machine tools. Therefore, the proposed indexes should be effective and sufficient for characterising the energy performance of a machine tool.

3.3. *Analysis and comparison of assessment indexes*

The existing indexes used to assess energy performance for developing energy-efficient machine tools and selecting appropriate machine tools in procurement processes can be divided into the following two categories: 1) the rated power or specific energy consumption at the machine component level for a predefined process, and 2) the energy demand at the machine tool

Table 1. Inherent energy performance indexes of a machine tool.

Index	Symbol	Description
Energy-consumption function indexes		
Standby power	$P_{\mathrm{sb},\,i}$	Power demand from the switching on of the main power and the running of electrical control systems to the starting of the spindle or main motor.
Starting energy function	$E_{\mathrm{st}}(n_i)$	Function relationship between starting energy consumption and spindle revolving speed (Huang, Liu, and Xie 2015).
Idling power function	$P_u(n_i)$	Function relationship between idling power and spindle revolving speed (Tuo et al. 2018).
Feed power function	$P_f(f_{vi})$	Function relationship between feed power and the corresponding feed rate.
Loading loss coefficient function	$\alpha(n_i)$	Function relationship between loading loss coefficients and spindle revolving speed.
Equivalent energy-consumption indexes		
Equivalent standby power	$\mathrm{EP}_{\mathrm{sb}}$	Weighted average of standby powers for different standby cases, $P_{\mathrm{sb},\,i}$. Weighting coefficient $C(P_{\mathrm{sb},i})$ is generally the corresponding occurrence probability. That is, $\mathrm{EP}_{\mathrm{sb}} = \sum C(P_{\mathrm{sb},i})P_{\mathrm{sb},\,i}$.
Equivalent starting energy	$\mathrm{EE}_{\mathrm{st}}$	Weighted average of starting energy at different objective spindle revolving speeds, $E_{\mathrm{st}}(n_i)$. The weighting coefficient is generally the usage frequency of revolving speed $C(n_i)$. Namely, $\mathrm{EE}_{\mathrm{st}} = \sum^{C}(n_i)E_{\mathrm{st}}(n_i)$.
Equivalent idling power	EP_u	Weighted average of idling powers at different spindle revolving speeds, $E_u(n_i)$, where the weighting coefficient is frequently the corresponding usage probability, $C(n_i)$. Namely, $\mathrm{EP}_u = \sum C(n_i)P_u(n_i)$
Equivalent feed power	EP_f	Weighted average of feed powers at different feed rates, $P_f(f_{vi})$, where the weighting coefficient is typically the corresponding feed rate probability, $C(f_{vi})$. That is, $\mathrm{EP}_f = \sum C(f_{vi})P_f(f_{vi})$
Equivalent loading loss coefficient	$E\alpha$	Weighted average of loading loss coefficients at different revolving speeds, $\alpha(n_i)$, where the weighting coefficient is frequently the corresponding usage probability, $C(n_i)$.That is, $E\alpha = \sum C(n_i)\alpha(n_i)$.

level for a reference workpiece. Compared with the former category, e.g. a plot at the component level for a reference process (ISO 2016; Schudeleit et al. 2016) or the horse power obtained from CNC Experts (Taha and Rostam 2011), the proposed energy-consumption function indexes are more elaborate and systematic because the specific energy consumption in a pre-defined process includes several energy performances related to the process, and not the energy performances resulting from process controls in the usage phase. Moreover, compared with the second category, e.g. the energy consumption at the machine tool level for a machining feature (Hu et al. 2015) or a standardised workpiece (Behrendt, Zein, and Min 2012), the proposed indexes are not only superior compared to the indexes at the component level but also consider the distribution of process controls. In summary, the existing methods derived for a reference workpiece are based on a specific process cycle for a certain task, while the proposed indexes are based on a reference process cycle for the task groups in product life cycle.

Regarding the selection and application of indicators, if an operational process (e.g. spindle revolving speed) is known prior to the selection or design of machine tools, the energy-consumption function indexes are recommended as they help in estimating the power demand at the target revolving speed to make accurate decisions. If the operational process is unknown, the equivalent energy-consumption indexes should be used because they are more representative compared to the indexes for a specific task from a statistical point of view.

4. Systematic acquirement method for IEP indexes

4.1. *Measurement method for basic data*

4.1.1. *Measurement boundary*

Conventionally, the measurement boundaries based on the method of energy exchange between a machine tool and its surroundings are generally divided into the following four types (ISO 2016), as shown in Figure 2: (1) electrical energy, (2) tube boundary supplied with an inlet measurement only, (3) tube boundary supplied with inlet and outlet measurements, and (4) other functions that are primarily supplied under the use of electrical energy. In this study, type 1 is adopted as the measurement boundary of the proposed measurement method in consideration of the time and cost of measurement because types 2–4 involve technical building services, which may not fundamentally belong to the intrinsic characteristics of the machine tool.

4.1.2. *Measurement process*

To obtain the proposed indexes systematically, a reference process is employed to measure basic data to calculate the indexes. The measurement process consists of the following two steps: First, the power demand of auxiliary components, such as

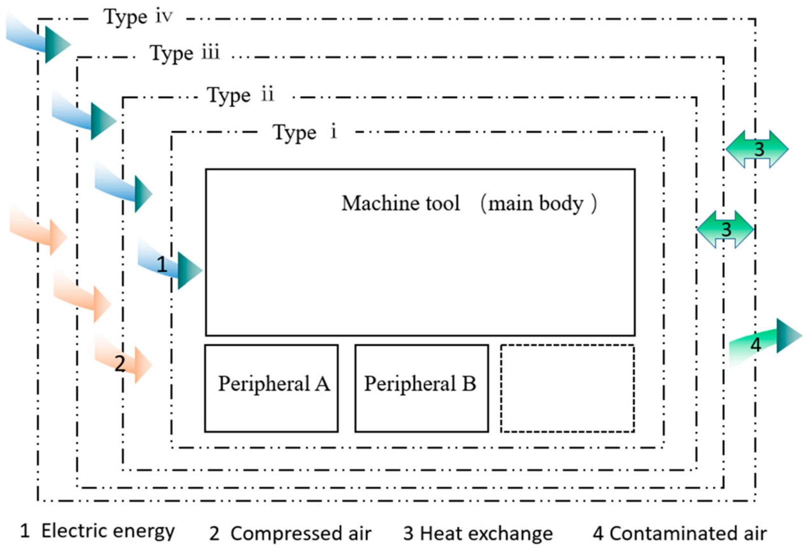

Figure 2. Measurement boundaries for machine tool.

Table 2. Measurement process for fixed power.

1	Initiate energy measurement[#]	4.3	… …
2	Turn on main switch	4.x	Turn on gas–oil separator
3	Turn on control panel		Turn off gas–oil separator
4.1	Turn on light system	5	Turn off control panel
	Turn off light system	6	Turn off main switch
4.2	Turn on hydraulic system	7	End of energy measurement
	Turn off hydraulic system		

#Only true for machine tools that are equipped with these components.

hydraulic systems, mist separators, and cooling systems, is measured to calculate the standby power for different cases. As the power demand of auxiliary components is constant even when cutting parameters or parts are changed, this power is also referred to as fixed power. Second, a machining process with a simple part is applied to obtain the power parameters related to dynamical systems, including spindle power, additional loss power, and feed axes power, as shown in Figure 1. These power parameters are typically referred to as variable power because their value changes with process controls.

An example of a measurement process for machine centres is as follows: The first step is illustrated in Table 2. A dwell time of 5 s is included between each step to identify the times when the power profile changes. After selecting the start and end points of the profile, power consumption is calculated based on the average of the profile. The control panel is not measured individually or regarded as a peripheral facility because it accompanies almost all processes or machine tool activities.

The second step is to acquire variable power. Considering the milling process as an example, the operation and tool path are shown in Figure 3 and Table 3. Because the power demands along the *X*- and *Y*-axes are almost the same in the positive (+) and negative (–) directions, the directions of the *X* and *Y* axes are not treated separately. Before machining, standby time T_1 can be increased to warm up the machine tool. Idling time T_2 is required to measure stable idling power. The air-cutting distance from the spindle site, which starts at the point where the tool touches the workpiece, is used to measure feed rate power. This distance is typically determined through the test feed rate and maximum travel distance of the machine tool. To acquire reliable data, idling time T_2 should be more than 5 s and the air-cutting distance should be more than 20 mm.

4.2. *Calculation of indexes from basic data to indexes*

4.2.1. *Establishment of database*

4.2.1.1. Data classification. The data for calculating the indexes can be divided into energy-correlated data (ECD) and operation-correlated data (OCD). ECD are directly related to the energy or power demand of machine tools during a specific

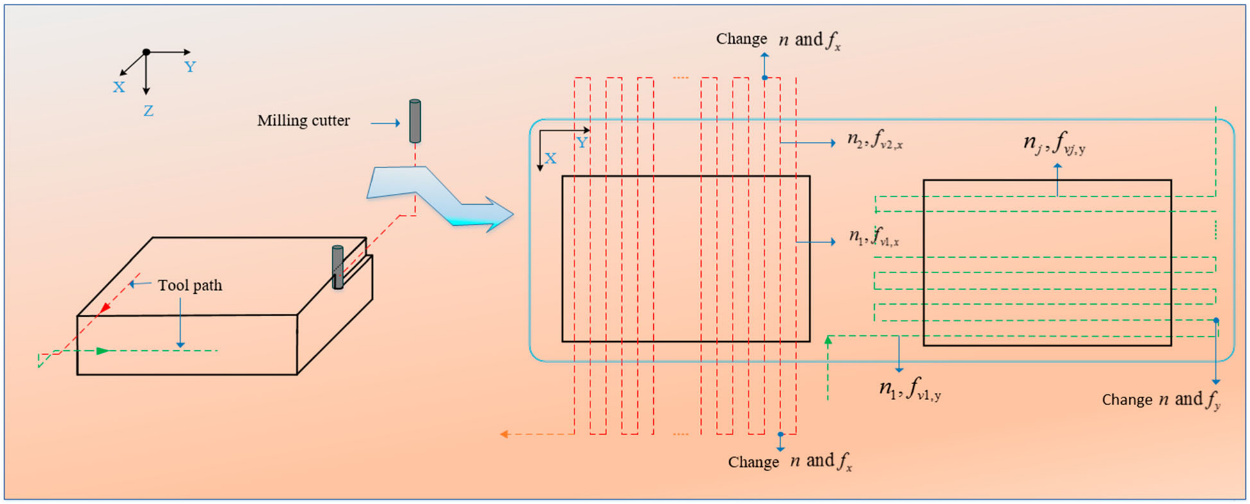

Figure 3. Energy-consumption measurement procedure for variable power.

Table 3. Energy-consumption measurement procedure for variable power.

1	Initiate energy measurement	5	Start spindle, feed drive (X-axis), cutting
2	Standby: T_1	5.1	Start spindle (n_i)
3	Travel Z(Z+) axis	5.2	Rotate on site: T_2
4	Start spindle, feed drive (X-axis), cutting	5.3	Travel X axis
4.1	Start spindle (n_i)	5.4	Travel Y axis ($f_{vi,y}$)
4.2	Rotate on site: T_2	5.5	Travel X axis
4.3	Travel Y axis	5.6	Change spindle revolving speed and feed rate (Y-axis)
4.4	Travel X axis ($f_{vi,x}$)	5.7	Repeat from 5.1
4.5	Travel Y axis	6	Travel Z (Z-axis)
4.6	Change spindle revolving speed and feed rate (X-axis)	7	End of energy measurement
4.7	Repeat from 4.1		

running process or activity, such as starting energy and the idling power at one speed. OCD are the operation data related to various process controls of machine tools, such as different standby cases and the corresponding occurrence probabilities and different spindle rotation speeds and the corresponding probability distributions during the service phase.

4.2.1.2. *Data collection*. ECD include the standby power, starting energy consumption, idling power, feed power, and loading loss coefficient of machine tools. The data collection methods for establishing an ECD database are shown in Figure 4.

Standby power consists of the constant power of a machine tool (main body) and peripheral components. Constant power refers to the power demand when the machine tool is switched ON without other components running, such as hydraulic and lighting systems. The power demand of the machine tool (main body) and peripheral components can be typically measured directly though the operations listed in Table 2.

Idling power and feed power can be directly measured based on the procedure given in Table 3. Starting energy is the energy consumption of the procedure from 0 rpm to the target rpm of the spindle, and it can be determined through Eq. (1).

$$E_{\mathrm{st}} = \sum_{T_{\mathrm{st}}}^{T_{\mathrm{end}}} P_{T_i} \Delta t \; (T_{\mathrm{st}} \le T_i \le T_{\mathrm{end}}) \tag{1}$$

where T_{st} and T_{end} denote the beginning and ending times of the spindle start-up process, respectively, P_{T_i} is the average power during time $[T_i, T_{i+1}]$, and Δt is the sample interval.

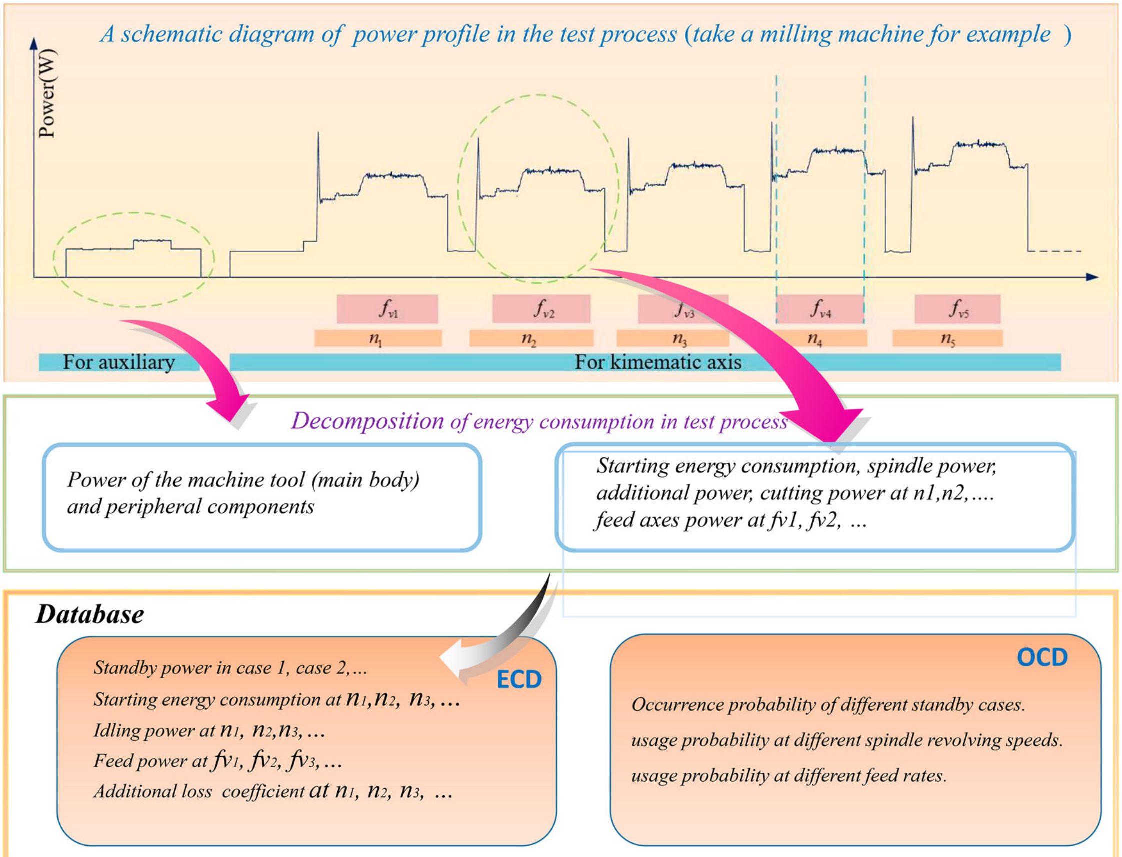

Figure 4. Process for establishment of database.

The value of P_a is occasionally difficult to measure directly, and it is generally obtained indirectly through Eq. (2) (Tuo et al. 2018).

$$\alpha = \frac{P_{\text{in}} - P_u - P_{\text{feed}}}{P_c} - 1 \tag{2}$$

OCD include the occurrence probability of different standby cases, the usage probability at different spindle revolving speeds, and the usage probability at different feed rates. The occurrence probability of a standby case is defined as the ratio of the running time of the standby case to the total running time of all standby cases. The usage probability at a feed rate is defined as the ratio of running time of the feed rate to the total running time of the feeding process. The usage probability at a spindle rotation speed is defined as the ratio of rotation time of the speed to the total rotation time of all spindle rotation speeds. These data can be acquired either through an automated approach and underlying artificial intelligence techniques or through consumer feedback.

4.2.2. *Calculation*

4.2.2.1. Energy-consumption function indexes. The energy-consumption function indexes include standby power, the starting energy function, idling power function, feed power function, and loading loss coefficient function.

The standby power of different cases can be measured individually or calculated after obtaining the constant power of the machine tool (main body) and peripheral components.

The starting energy function of a machine tool is related to spindle rotation. For a step-speed-regulation machine tool, starting energy can be derived using respective measurements, and the starting energy function can be expressed using a finite set. For a stepless-speed-regulation machine tool with continuous spindle rotation, the starting energy function can be determined by measuring the energy consumption at several selected speeds, followed by constructing the fitting energy consumption function with speed as a variable, as shown in the following equation:

$$E_{\mathrm{st}} = \mathrm{An}^2 + \mathrm{Bn} + C \tag{3}$$

where A, B, and C are curve-fitting coefficients.

The method of acquiring the idling and feed power functions is similar to that for the starting energy function. The idling power function index can be acquired by establishing the idling power function with spindle rotation speed as a variable. The feed power function index can be acquired by establishing the feed power function with feed rate as a variable.

The relationship between the loading loss coefficient and rotation speed is complex and difficult to fit, and fitting error may be unsatisfactory. Thus, the loading loss coefficient is typically advised to be measured at a defined rotation speed, with the corresponding function expressed using a finite set.

4.2.2.2. *Equivalent energy-consumption indexes*. The equivalent energy-consumption indexes involve equivalent standby power, equivalent starting energy, equivalent idling power, equivalent feed power, and the equivalent loading loss coefficient.

Equivalent standby power represents the average power demand in standby states during the usage phase of machine tools, and it is typically calculated by utilising the following model:

$$\mathrm{EP}_{\mathrm{sb}} = \sum_{i=1}^{i=m} C(P_{\mathrm{sb},i})P_{\mathrm{sb},\,i} \tag{4}$$

where $\mathrm{C}(P_{\mathrm{sb},i})$ indicates the occurrence probability of standby case i, $P_{\mathrm{sb},i}$ is its power demand, and m is the total number of standby cases.

Equivalent starting energy describes the energy consumption in spindle start-up process of machine tools, and it can be acquired using Eq. (5). Similarly, equivalent idling power and the equivalent loading loss coefficient can be estimated using the Eq. (6) and Eq. (7), respectively, after obtaining the idling power and loading loss coefficient at any revolving speed.

$$\mathrm{EE}_{\mathrm{st}} = \sum_{i=1}^{i=k} C(n_i)E_{st}(n_i) \tag{5}$$

$$\mathrm{EP}_u = \sum_{i=1}^{i=k} C(n_i)P_u(n_i) \tag{6}$$

$$E\alpha = \sum_{i=1}^{i=k} C(n_i)\alpha(n_i) \tag{7}$$

where $\mathrm{C}(n_i)$ indicates the usage probability at spindle rotation speed n_i, and $E_{\mathrm{st}}(n_i)$, $P_u(n_i)$, and $\alpha(n_i)$ denote starting energy, idling power, and the loading loss coefficient, respectively. k is the total number of spindle rotation speeds.

Equivalent feed power is the weighted average of the feed power at different feed rates. For example, the equivalent feed power for the X feed axis is acquired through Eq. (8). The equivalent feed power for the other feed axis is obtained in a similar manner.

$$\mathrm{EP}_{f,x} = \sum_{i=1}^{n} C(f_{vi,x})P_f(f_{vi,x}) \tag{8}$$

where $\mathrm{C}(f_{vi,x})$ denotes the usage probability at feed rate $f_{vi,x}$, and $P_f(f_{vi,x})$ is the feed power of $f_{vi,x}$. n is the total number of feed rates.

5. Case study and potential application

5.1. *Experimental setup*

A CNC milling centre was selected as a case study, and the selected workpiece for acquiring the basic data was an aluminium plate with a width of 200 mm, a length of 250 mm, and a height of 30 mm. In addition, four counterbores were used for fixing the sensor onto the workpiece. A force measurement tool consisting of a sensor, a charge amplifier, and a data acquisition system was used to measure cutting forces, which were used to calculate cutting power and ultimately acquire the loading loss coefficient. An HC3390 power analyser with a sampling frequency of 500 kHz was employed to acquire power data, as shown in Figure 5.

5.2. *Results and discussion*

In the case study, the constant power of the machine tool (main body) for the milling centre was 323 W on average and that of the hydraulic system was 92 W. Idling power is a function of spindle rotation speed, and it generally increases with speed. Figure 6 shows that there are two shifts in idling power at 2,400 and 2,800 rpm. These shifts may be caused by the shift in the spindle gear. Based on the fitting curves shown in Figure 6, the starting energy of the stepless-speed-regulation machine tool can be represented as a quadratic function of spindle rotation speed. The fitting results are considered as the idling power function and starting energy function, as shown in Table 4.

The feed power of the CNC milling centre was measured along the *X*-axis and *Y*-axis but not along the *Z*-axis owing to low power consumption and low variability. The power demands for the *X*-axis and *Y*-axis movements at defined feed rates are shown in Figure 7. Compared with spindle power, P_{spindle} (acquired by subtracting standby power (415 W) from the idling power shown in Figure 6), the power demand for only the *X*-axis and *Y*-axis, P_{feed} (acquired by subtracting standby power (415 W) from the feed power shown in Figure 7), is considerably low. This may be why the power of the spindle motor is occasionally considered and the power demand of the feed drive motor is neglected. The fitting results shown in Figure 7 were also considered as a feed power function in the case study, as indicated in Table 4. In addition, owing to the complexity and fitting error of the CNC milling centre, only the loading loss coefficients at the representative spindle rotation speed were selected, the results of which are shown in Table 4.

OCD were estimated by interviewing the handlers of Chongqing Machine Tools (Group) Co., Ltd., China. Two standby cases (power on only, and power on and hydraulic system on) were included. Nine representative spindle rotation speeds and four representative feed rates were selected to calculate the equivalent energy-consumption indexes. All IEP indexes were calculated based on the ECD and OCD mentioned above, the results of which are shown in Table 4.

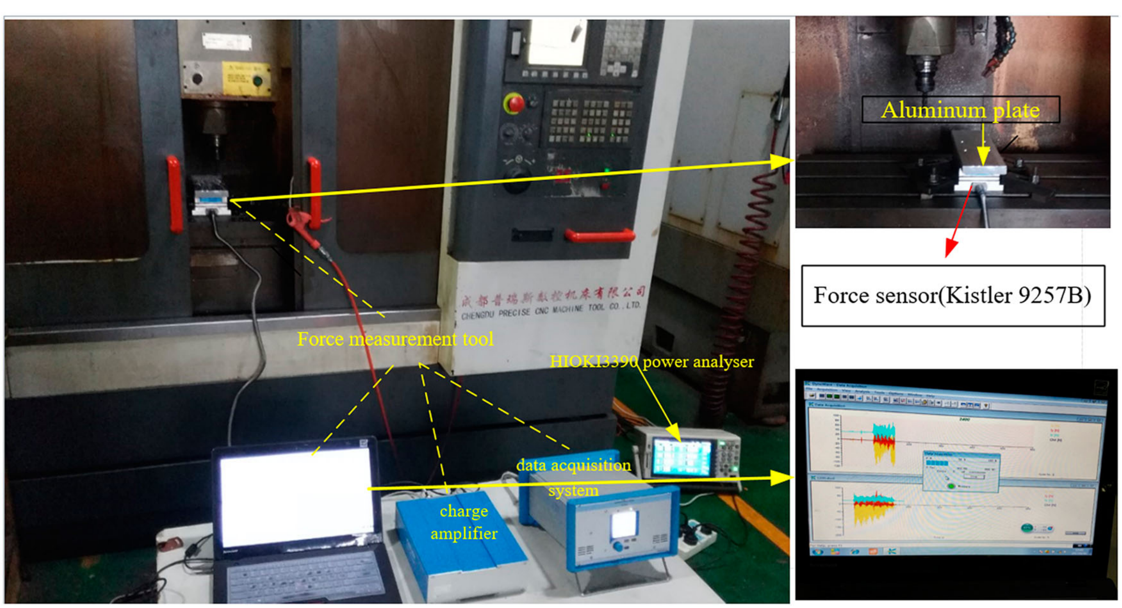

Figure 5. Experimental machining site at CNC milling centre.

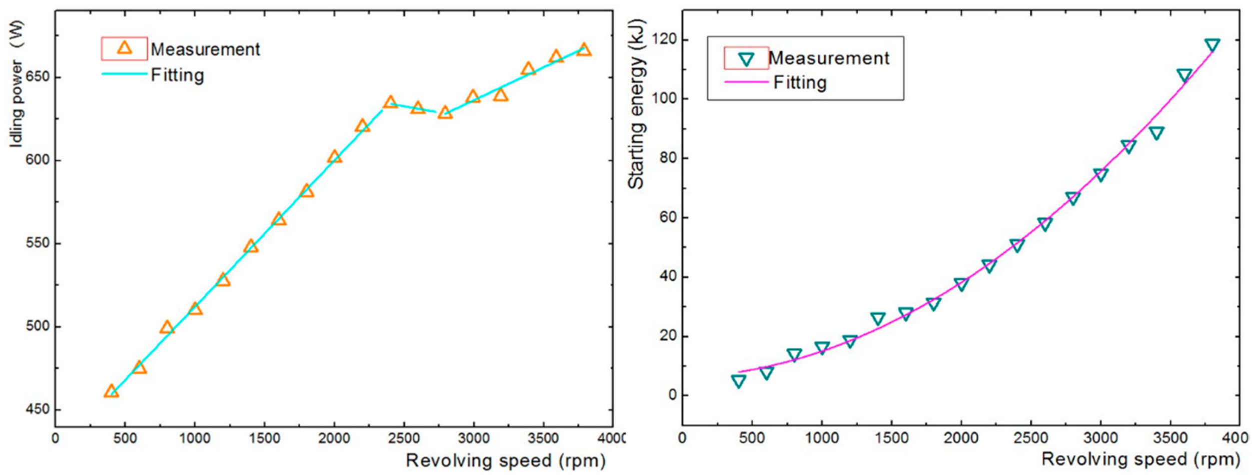

Figure 6. Idling power and starting energy at defined spindle rotation speeds.

Table 4. IEP indexes of CNC milling centre.

Energy-consumption function indexes	
Standby power (W)	$P_{\text{sb},i} = \{323, \ \ 415\}$
Starting energy function (kJ)	$E_{\text{st}}(n) = 7.15 \times 10^{-6}n^2 + 1.77 \times 10^{-6}n + 6.17, \ \ n \in [200, \ \ 4000].$
Idling power function(W)	$P_u(n_i) = \begin{cases} 8.80 \times 10^{-2}n + 424.36, \ \ n \in (200, 2400] \\ -1.49 \times 10^{-2}n + 670, n \in (2400, 2800] \\ 3.96 \times 10^{-2} + 517.63, n \in (2800, 4000] \end{cases}.$
Feed (X) power function (W)	$\text{EP}_{\text{fx}}(f_{vi,x}) = 1.15 \times 10^{-2}n + 421.58, f_{vi,x} \in [40, 450].$
Feed (Y) power function(W)	$\text{EP}_{\text{fy}}(f_{vi,y}) = 8.82 \times 10^{-3}n + 422.61, f_{vi,y} \in [40, 450].$
Loading loss coefficient function	n :200, 600, 1000, 1400, 1800, 2200, 2600, 3000, 3600; α :0.27, 0.24, 0.08, 0.17, 0.20, 0.11, 0.09, 0.16, 0.10.
Equivalent energy-consumption indexes	
Equivalent standby power	396.6 W
Equivalent starting energy	37.26 kJ
Equivalent idling power	565.15 W
Equivalent feed power (X axis)	424.28 W
Equivalent feed power (Y axis)	424.20 W
Loading loss coefficient function	0.137

5.3. *Potential application*

5.3.1. *Application I: energy label*

An energy label acts as a description or complement to an energy efficiency test or evaluation. It is typically affixed to products and their packaging, and it contains information on the energy efficiency or energy consumption of products (Shi 2014). With respect to a machine tool, information labels are generally effective for economically and/or environmentally concerned consumers, and they are accepted more by manufacturers and consumers (Mahlia and Saidur 2010). As the IEP indexes involve the energy demand information of almost all machine system activities and states, it is a good choice to include the indexes in the content of energy labels, as shown in Figure 8. The designed QR code shown in the bottom-right corner is provided for the consumers and/or designers of the machine tool who require detailed energy information.

5.3.2. *Application II: selection of machine tool*

Selecting a matching machine tool for saving energy typically involves the following two cases: selecting suitable machining equipment for optimising a production schedule prior to manufacturing and selecting a suitable machine tool when new

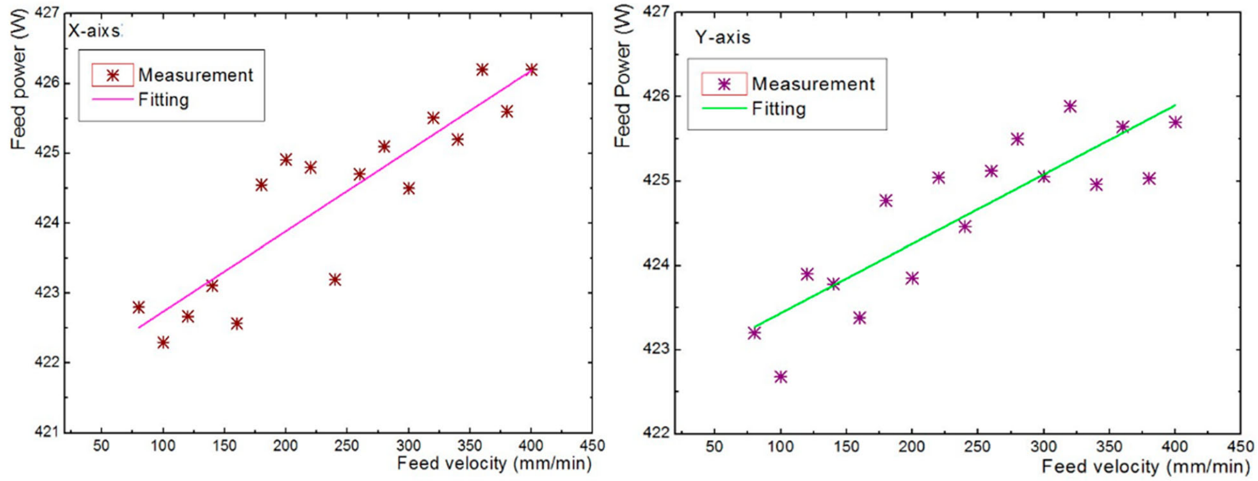

Figure 7. Feed power for the *X*-axis and *Y*-axis at corresponding defined feed rates.

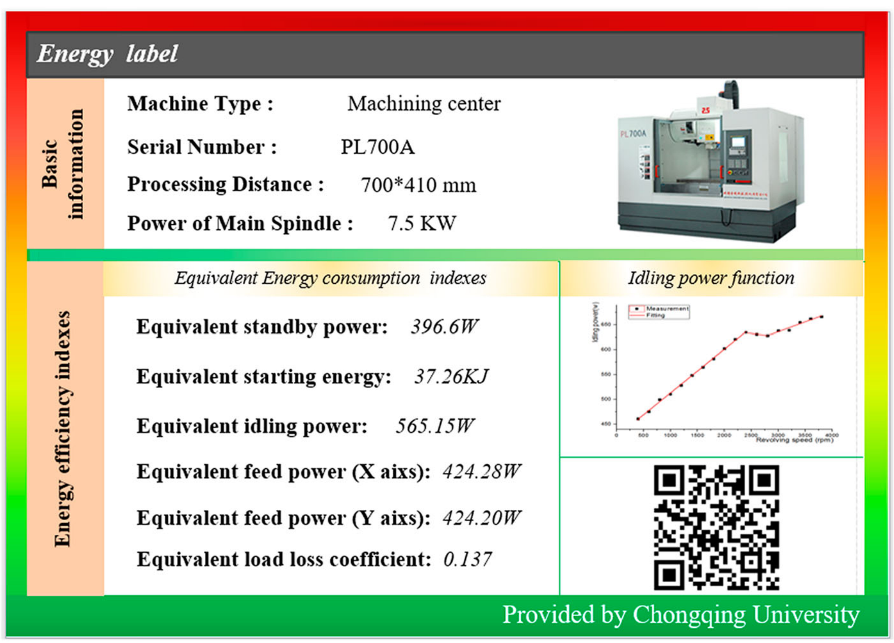

Figure 8. Energy label for the CNC machining centre used in the case study.

production sites, such as machining workshops and production lines, are built. In the first case, by combining a machining file with the energy-consumption function indexes, the energy demand for each given production schedule or cutting parameter can be predicted (Li et al. 2014). Then, the most appropriate machine tools for saving energy can be determined based on the predictions. The second case is referred to as selecting appropriate machine tools in procurement processes. As an example, we consider the selection of a high-speed dry-cutting gear-hobbing machine for Chongqing Landai Powertrain, Corp., Ltd., China (Liu et al. 2018.). The results of different methods, including the proposed method, are shown in Table 5. As the idling energy consumption of the gear-hobbing machine generally accounts for more than 80% of total energy consumption (Cao et al. 2017), equivalent idling power is selected as an evaluation index. Different from the conventional method, which is applied for low-standby machine tools, YE3120CNC7 was recommended to build the production line using the proposed method, which is consistent with the decision making introduced by Liu et al. (2018) for achieving higher energy efficiency.

Table 5. Evaluation results of two different methods.

Method	Conventional method	Proposed method
Indexes	Standby power (W)	Equivalent idling power (W)
YE3120CNC7	3442	5496
YS3120CNC7	2378	6106

5.3.3. *Application III: development of energy-efficient machine tool*

The development of an energy-efficient machine tool can help improve energy efficiency during the entire service period (Tian et al. 2017). The equivalent energy-consumption indexes can be considered as a reference for estimating the power demand during the usage phase. This is a significant step for designing an energy-efficiency machine tool (Duflou et al. 2012). Moreover, equivalent standby power could be applied to a selection criterion for auxiliaries, such as lubrication systems and air conditioners, for efficient design owing to its more accurate evaluation. Equivalent idling power is more suitable for selecting a spindle motor because spindle rotation speed and its distribution, which are important factors, are considered.

6. Conclusion

Considering the energy consumption of machine tools, particularly in the manufacturing industry, which consumes considerable amounts of energy, competitiveness can be improved, innovation can be promoted, and several economic and environmental advancements and sustainability can be achieved. The key performance indicators used to assess the energy performance of a machine tool in a systematic manner are generally considered as a prerequisite for energy saving research, such as the optimisation of machine tool design and selection. This paper proposed a group of energy-related key performance indicators to support the development of energy-efficient machine tools and the selection of matching machine tools, in consideration of the major challenge of the impact of process controls in the usage phase. A systematic method for acquiring the IEP indexes, including the measurement of basic data and the calculation of the indexes from basic data, was introduced. In addition, the results of a case study suggested that the proposed indexes include the energy demand information of almost all machine tool activities. This is helpful for developing energy labels, selecting matching machine tools, and designing energy-efficient machine tools.

The contributions of this work can be categorised into three aspects. First, a group of energy-related key performance indicators referred to as the IEP indexes are proposed to systematically assess the IEP of machine tools. Among these indexes, the energy-consumption function indexes can provide detailed energy consumption data and the equivalent energy-consumption indexes present comprehensive mean energy information. Second, a simplified measurement with a simple workpiece is introduced to acquire the detailed energy data of machine tools. Such energy data are used to calculate the IEP indexes in this study, and they are widely applicable to other energy research such as the prediction and/or simulation of energy demand for a machine tool. Finally, a model is presented to calculate the indexes from basic data. It involves the establishment of a database and the calculation of the IEP indexes.

A limitation of this work is that the proposed indexes are mainly suitable for metal-cutting machine tools and not all types of machine tools. Furthermore, the OCD collected from a single enterprise in the case study may be insufficient from a statistics perspective. Future work will involve the development of new methods for acquiring exact OCD though an automation approach and underlying artificial intelligence techniques.

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