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A dynamic approach for life cycle global warming impact assessment of machine tool considering time effect

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Abstract

Purpose Machine tools are the equipment used for the cutting and shaping of materials, like metals, which generate greenhouse gas (GHG) emissions across their life cycles due to material use and energy consumption. The life cycle emissions of machine tools are distributed over time and may vary with technology advancement. This paper aims to incorporate these temporal factors into the global warming impact (GWI) assessment of machine tools and further reveal their influences on the results.

Method Incorporating emission time into the GWI assessment of machine tools is based on the following dynamic LCA framework. First, compute temporally-differentiated GHGs of machine tools based on the activity-based modelling. And then, use time-dependent characterization factors (CFs), which is developed based on the radiative forcing concept, to assess their GWI. By using this framework, a dynamic life cycle GWI assessment of machine tool is conducted using two gear hobbing machines. Both the emission time and the potential changes of life cycle emissions due to the improvement of electricity mix and the variation of machine tool use modes are considered.

Results and discussion The results demonstrated that when the emission time was considered, both machines offered 3% of reduction of GWI, compared with their static results, respectively. Further reductions were found for the two machines, when the electricity improvement and the changes of the machine tool use modes were considered. All the differences between the static and the dynamic environmental impact results become smaller with the extension of the time horizons (THs) that accounted for the evaluation.

Conclusions and recommendations The conventional static LCA has the potential to overestimate the real GWI of machine tools. It is more important to account for the emission time in GWI assessment at shorter THs or for a longer lifetime of machine tools. This work offers a method to dynamically assess the real GWI of machine tools. The proposed method helps to make robust decision-making for environmentally-friendly machine tool selection and support sustainable production.

Keywords: Time effect; Dynamic life cycle assessment; Machine tool; Cumulative radiative forcing; Global warming potential; electricity mix

1. Introduction

Across all industrial activities, manufacturing contributes to approximately 36% of global CO_2 emissions and 33% of worldwide electricity consumption (Ibbotson and Kara 2018). In China, the

manufacturing sector even contributes about 55% of the total energy consumption (NBS 2017). Machine tools are widely used as the basic production equipment of the manufacturing industry. In recent years, the annual output of metal cutting machine tools has been more than 0.6 million in China, ranking first in the world for many years (NBS 2019). Reducing the energy consumption and the carbon emissions of machine tools are of great importance for the energy conservation and carbon emission mitigation of the entire manufacturing industry. They have been widely concerned by the machine tool manufacturers and the Chinese government.

Life cycle assessment (LCA), as a quantitative analytic tool for environmental impact, plays an important role in environmentally-friendly machine tool optimization and selection. Many studies have been focused on the machine tools LCA. Cao et al. (2012) established calculation models for the life cycle carbon emissions assessment of machine tools and proposed three carbon efficiency indicators to characterize their carbon emission performance. Two alternative machine tools were compared and the one with higher carbon efficiency was determined. Diaz et al. (2010) compared the energy consumption and the carbon emissions of two milling machine tools in various manufacturing environments, i.e. a community shop, a job shop, and a commercial facility. They concluded that the use phase comprised the majority of the overall emissions but highly relied on the facility types. Züst et al. (2016) developed an effective tool to quantify the energy consumption of machine tools during their whole life cycles. The tool was used to identify the hotspots of three exemplary machine tools and measures to increase their energy efficiency were derived. In order to assist the SMEs to perform environmental impact assessments of machine tools and implement eco-design, Krautzer et al. (2015) developed a rough LCA tool, achieving a quick acquisition of the overall representative environmental impact profiles of machine tools. Zeng et al. (2018) proposed a framework for eco-design decision making of machine tool based on LCA. In this framework, the hotspots for carbon emission mitigation were identified first and then the optimal measures were determined by sensitivity analysis.

The above-mentioned studies aimed to quantify, compare, or optimize the energy and carbon emissions of machine tools based on the LCA. However, they exclusively followed the conventional static LCA, without considering the emission time. In reality, the activities associated with machine tool production, use and disposal take place gradually over time. Therefore, the emissions during the life cycles of machine tools are distributed over time, as shown in Fig.1. In the conventional static machine tools LCAs, the same GHG emissions are directly aggregated, disregarding the time they occur, to calculate their global warming impact (GWI) by multiplying their corresponding characterization factors (CFs). Currently, the commonly used CFs are proposed by the Intergovernmental Panel on Climate Change (IPCC 2007), i.e., the relative cumulative radiative forcing (CRF) of per unit of GHG over a specific time horizon (TH) to that of the reference gas of CO_2 (more details about this method can be seen in Note 1 in Supporting Information (SI)). If all the GHGs of machine tools are regarded to emit at the same time, usually at the beginning of the life cycles, and the same THs are used to calculate their GWI, different reference time for the evaluation is accounted, as shown in Fig. 1. This can lead to inconsistency in time frames for GWI assessment and potentially create misleading results.

Currently, the LCA practitioners use a generic dynamic GWI assessment methodological framework to address the temporal inconsistency in the conventional static LCA. The temporally differentiated life cycle inventories (LCIs) are computed first, and then, their GWI is assessed using the time-dependent CFs. Up to now, many methods have been developed to calculate the temporally differentiated LCIs, mainly including the conventional matrix inversion, the enhanced structural path analysis, and the direct traversal methods (Beloin-Saint-Pierre et al. 2014; Cardellini et al. 2018; Collinge et al. 2013; Tiruta-

Barna et al. 2016). In order to maintain consistency in the evaluation time of GWI, the later GHG emissions occur, the smaller the time periods should be accounted for their GWI calculation. Thus, the GHGs emitting later contribute less than those emitting earlier on the GWI. To reflect the impact of per unit mass of GHGs occurring at different times on the climate change, some time-dependent dynamic CFs, such as the time correction factor (Kendall et al. 2009; Kendall and Price 2012), the time-adjusted factor (Kendall 2012; Yu et al. 2018) and the time-dependent CFs (Levasseur et al. 2010), have been proposed and used. In this paper, followed by the dynamic GWI assessment framework, the temporally-differentiated LCIs of machine tools are calculated first and then the GWI of machine tools are calculated in terms of time-adjusted CRF (TCRF) and GWP (TGWP), respectively. The dynamic life cycle global warming impact assessment method used in this paper is described in detail in Section 2.

Apart from the overlooked emission time in the current machine tool LCAs, there is another deficiency, that is, the dynamic changes of the emissions over the life cycles of machine tools are also not considered. Regarding the long lifetime of machine tools, the inventories that take place in the future have the potential to be changed due to technology development. For example, the greenhouse gas (GHG) emissions from the operation of machine tools are projected to be reduced with the annual improvement of the electricity mix. This would significantly reduce the total carbon emissions of machine tools, considering the carbon emissions from electricity usage dominate the total life cycle carbon emissions. In addition, the working conditions, such as the application of various use modes, have a significant influence on the GWP of machine tools (Diaz et al. 2010). Addressing these dynamic changes of the emissions over the life cycles of machine tools is important to reduce uncertainty and improve the credibility of the LCA results. Thus, they are also incorporated into the machine tool LCA in this paper.

2. Methods

2.1. Dynamic global warming impact assessment method of machine tool

To overcome the temporal inconsistency in the conventional GWI assessment, the time-dependent CFs should be introduced for the calculation of GWI of GHGs emitting at different times. The total GWI of machine tools can be obtained by the dot product of the temporally-differentiated GHGs and the corresponding time-dependent CFs, as shown in Eq. (1). For simplicity, considering the high temporal resolution of GHGs is not required for the GWI calculation (Shimako et al. 2018), the GHGs are differentiated by a discrete year to form the yearly-distributed GHGs of machine tools.

$$\mathrm{GWI}=\mathbf{G}_t \bullet \mathbf{CF}_t \tag{1}$$

$$\mathbf{G}_t = \begin{bmatrix} g_{\mathrm{CO_2},1} & g_{\mathrm{CO_2},2} & \cdots & g_{\mathrm{CO_2},t_e} \\ g_{\mathrm{CH_4},1} & g_{\mathrm{CH_4},2} & \cdots & g_{\mathrm{CH_4},t_e} \\ g_{\mathrm{N_2O},1} & g_{\mathrm{N_2O},2} & \cdots & g_{\mathrm{N_2O},t_e} \end{bmatrix} \tag{2}$$

$$\mathbf{CF}_t = \begin{bmatrix} CF_{\mathrm{CO_2},1} & CF_{\mathrm{CO_2},2} & \cdots & CF_{\mathrm{CO_2},t_e} \\ CF_{\mathrm{CH_4},1} & CF_{\mathrm{CH_4},2} & \cdots & CF_{\mathrm{CH_4},t_e} \\ CF_{\mathrm{N_2O},1} & CF_{\mathrm{N_2O},2} & \cdots & CF_{\mathrm{N_2O},t_e} \end{bmatrix} \tag{3}$$

where $\mathbf{G}_t$ is the yearly-differentiated GHGs that can be expressed as Eq. (2). Each row corresponds to the emission quantities of a GHG (e.g., kg of CO_2) and each column corresponds to a one-year step, t_e is the end-of-life time of machine tools, while $\mathbf{CF}_t$ is the matrix of CF that can be further represented as

Eq. (3). Each row corresponds to the GWI of per kilogram of a GHG (e.g., GWI of per kilogram of CO_2), and each column corresponds to a one-year step.

The CFs developed in the static GWI assessment in terms of CRF and GWP (see Note 1 in SI) are not time-dependent. Therefore, multiplying these CFs by the temporally-differentiated GHGs directly to calculate the GWI of the machine tool can cause temporal inconsistency. To maintain the consistency, for the *i*th GHG emitting at year *j*, its corresponding CRF calculation is further adjusted as Eq. (4), according to Levasseur et al. (2010), where the upper limit of the integration changes to *TH-j*. By substituting the corresponding value in Eq. (3) in Note 1, the CF of the *i*th GHG emitting at year *j*, in terms of TCRF can be calculated as:

$$TCRF_{i,j} = \int_0^{TH-j} \alpha_i \times C_i(t)dt \tag{4}$$

where $TCRF_{i,j}$ is the time-adjusted CRF of the *i*th GHG emitting at year *j* and α_i represents the radiative efficiency of the *i*th GHG. For the main GHGs CO_2, CH_4 and N_2O, the radiative efficiency per unit mass are 1.82×10^{-15}, 1.82×10^{-13} and 3.88×10^{-13} $Wm^{-2}kg^{-1}$ (Fuglestvedt et al. 2010), respectively, while $C_i(t)$ represents the decay function of the *i*th GHG that is determined in Note 1.

Eq. (4) characterizes the dynamic GWI of a machine tool in units of TCRF. To keep in line with the global warming potential (GWP) indicator proposed by IPCC (see Note 1), the time-adjusted GWP (TGWP) indicator is further adopted in this paper, as shown in Eq. (5) (Kendall 2012). The default TH of 100 years recommended by IPCC is applied in this work. The effect of the application of various THs is discussed in Section 5.1. Table S1 lists the time-dependent CFs in terms of TCR and TGWP with a TH of 100 years. It can be seen from the table that the later the GHG emissions occur, the smaller the corresponding CFs in terms of TCR and TGWP.

$$TGWP_{i,j} = \frac{TCRF_{i,j}}{\int_0^{TH} \alpha_{CO_2} \times C_{CO_2}(t)dt} \tag{5}$$

where $TGWP_{i,j}$ is the time-adjusted GWP of the *i*th GHG emitting at year *j*.

2.2. Implementation procedures

Following are the four steps to implement the calculation of dynamic GWI of machine tools mentioned above: 1) determining the temporal scale of machine tools throughout their whole life cycles; 2) compiling the yearly-differentiated life cycle GHG emissions on the temporal scale; 3) quantifying the time-dependent CFs and 4) calculating the GWI of machine tools based on the time-dependent CFs. A detailed description of each step is given below.

Step 1: Determining the temporal scale of machine tool LCA.

The first step to realize the dynamic GWI assessment of machine tools is to determine the temporal scale of the whole life cycles of machine tools. The temporal scale of an LCA covers the time from cradle to grave, typically including raw materials acquisition, materials production, product manufacturing, product use, end of life (EoL) as well as time lags in between (Yuan et al. 2015). The raw materials acquisition, the materials production, and the product manufacturing share similar features for the time durations of activities and the Critical Path Method (CPM) can be used to determine their time durations (Abdullah et al. 2012; Yuan et al. 2009). Regarding the machine tools use time, it can be determined by the design lifetime of machine tools, which is an expected lifetime under specific working conditions. The design lifetime is usually given in the design of the machine tools. The time durations of EoL treatment of machine tools can be estimated by the time consumed in the collection, disassembly, and

recycling. The time lags between the two life cycle stages include the time consumed by the transportation activities or time kept in inventory. They can be estimated using the fitted empirical functions, the panel judgments, or the pertinent databases (Yuan et al. 2015).

Step 2: Compiling the yearly-differentiated life cycle GHG emissions on the temporal scale.

Generally, the various GHG emissions during the life cycle of a machine tool are generated from both the resource and energy consumption of the activities associated with raw materials acquisition, materials production, machine tool manufacturing, use, and EoL disposal. Thus, the GHG emissions of all the activities constitute the emission profile of a machine tool. Activity-based modeling provides an effective way to link the emissions to specific activities and can be used to construct the temporally-differentiated life cycle GHG emissions on the temporal scale of a machine tool (Russell-Smith and Lepech 2012). After analyzing the temporal scale of machine tool LCA in Step 1, the time at which all the activities and their emissions occur can be determined. Then, those emissions of all the activities generated in the same year can be directly summed to form the yearly-differentiated life cycle GHG emissions. Many existing LCA tools, including SimaPro and Gabi, support the activity-based modeling and also provide the activity-based LCI datasheet. For example, Table S2 shows the GHG emissions of producing 1 kg of steel in SimaPro with Ecoinvent database v.3.5. The GHG emissions from producing the total steel can be calculated by multiplying it by the amount of steel used in the machine tool. Similarly, the GHG emissions in the machine use stage can be calculated by multiplying the total amount of resource and energy consumed by the corresponding GHG emissions per unit of resource and energy consumption (which is also from the Ecoinvent database v.3.5.). Thus, the activities generated in the same year can be modeled in the LCA tools to calculate the corresponding GHG emissions in that year. The database can be used as a data source for the background activities.

Steps 3 and 4: Quantifying the time-dependent CFs and calculating the GWI of machine tools based on the time-dependent CFs.

After obtaining the yearly-differentiated life cycle GHG emissions of machine tools, the time-dependent CFs in terms of TCRF and TGWP need to be quantified, according to Eqs. (4) and (5), respectively. Then, the GWI of machine tools can be calculated by the dot production of yearly-differentiated GHGs and CFs, as shown in Eq (1).

3. Case study

3.1 Goal and scope

A gear hobbing machine YDE3120CNC (hereinafter referred to as YDE) and its counterpart YS3118CNC5 (hereinafter referred to as YS) were selected as a case to illustrate the dynamic GWI assessment method and further explore the time effect on the LCA results. The YDE is a new generation of hobbing machine developed by Chongqing Machine Tools Works Co., Ltd, China. It is highly efficient and does not consume any cutting fluid. The YDE is regarded as a good substitution for the conventional wet hobbing machine of YS. Thus, this work applied the dynamic LCA method to assess its GWI and further investigated the environmental benefits of the new hobbing machine compared with the conventional one in a dynamic context.

The main technical parameters of the two machines are listed in Table 1. The design lifetime of the two machines is 10 years, under the context of working two shifts a day. The functional unit was defined as producing one piece of gear. The case considered all of the life cycle stages of the machine tools, including material extraction and manufacturing, i.e., cradle to gate (CTG), use, and EoL, as shown in

Fig.2. Moreover, the electricity mix was expected to improve over time due to the gradual deployment of clean energy-based electricity. The use and disposal of machine tools taking place in the future will benefit from the improvement of the electricity grid. Thus, they need to be incorporated in the machine tool LCA. Furthermore, to explore the influence of the variations of usage scenarios of the machine tool on the LCA results, two use modes of machine tools, i.e., operating two shifts a day (corresponding to mass production) and operating one shift a day (corresponding to small batch production) were studied in this case. The rationality behind the consideration of the variations of machine use modes of machine tool for dynamic GWI assessment is detailed in Note 2 in SI. Four scenarios were designed to study the time effect on the LCA results, as shown in Table 2.

In the present case study, SimaPro was used for the activity-based system modeling of machine tools in order to obtain the yearly-distributed GHG emissions and Ecoinvent database v.3.5 was used as the data source for the GHG emissions of the background processes. Notably, only the GHGs, including CO_2, CH_4, N_2O, were considered in this case.

3.2 Temporal scale of the whole life cycles of the machine tools

The calendar year of 2019 was selected as the initial time of the LCAs in the case study, which represented the starting time of material extraction of machine tools. The complete life cycles of the two sample machines will roughly go through the following stages: firstly, the primary materials that make up the two machines will be produced in the upstream raw material processing enterprises, and then they will be shipped to the machine tool manufacturer Chongqing Machine Tools Works Co., Ltd to produce the machine tools. After that, the machines will be delivered to the machine tool users for gear production until they are scrapped at the EoL stage. Lastly, both machines will be shipped to a dedicated company for recycling.

The material extraction and processing stage involves a series of production activities of the machine tool material, including steel, aluminum, and copper, etc. According to Yuan et al. (2009), the minimum time duration for these materials extraction and processing is estimated to be 0.26 years using the CPM. However, in practice, the time duration can be longer if all of these production activities are not conducted parallelly. The machine tool manufacturing stage includes parts manufacturing, component assembly, machine tool assembly, and quality check. Based on the manufacturing time of other existing similar machines, it is estimated that the manufacturing time of the two sample machines used in the case study is 0.42 years, of which parts manufacturing takes 0.25 years. In addition, material and machine tool storage also take some time to maintain the reliability of the supply chain. To sum up, it is conservatively estimated that it will take about one year to manufacture and deliver the two machines to the machine tool users. Thus, the emissions of the activities associated with material extraction, material processing, and machine tool manufacturing can be directly summed to form the first year of GHG emissions.

The time duration of the two machine tools in the use stage is strongly dependent on their use scenarios. Under the current design conditions, the two machines can operate two shifts per day for 10 years. While theoretically, if the machines operate one shift per day, they can run for another 10 years. That is, the time duration of the two machine tools in the use stage is 20 years. Furthermore, the disposal of the two machine tools in their EoL stages is expected to take place in the year after the end-use of the machine tools.

Fig. 3 shows the time frames of the whole life cycles of the two machine tools, under two different use scenarios.

3.3 Data collection over the temporal scale

The machine tools under investigation are composed of machine beds, columns, spindles, X/Y axes, pumps, coolers and control devices, etc. Based on the bill of material (BOM) of machine tools, six main types of materials of the two machine tools with their weight were obtained, as shown in Table S3 in SI. It can be seen from the table that cast iron contributes to most of the total weight of the machine tools. In this case study, the blast furnace and basic oxygen furnace (BF-BOF) route was selected for the primary steel production in this case, whose emissions came from the Ecoinvent v.3.5. The European manufacture data of the above materials in the Ecoinvent v.3.5 was used, but the main energy sources in the data such as electricity and hard coal were replaced with the Chinese data. Since the machine tool manufacturing stage contributes little to the total life cycle GHG emissions (Zeng et al. 2018), and it is difficult to obtain the energy and material consumption data during the manufacturing of machine tools under development, the emissions from the machine tool manufacturing were ignored in this case study.

The electricity and resources consumption was considered to be the same for each year during the machine tool use stage. It was estimated based on the power, resources consumption rates and operation time of the two machine tools. Table S4 and S5 list the inputs and the outputs of the two machine tools in the use stage under the two considered use scenarios, respectively. The LCI modeling of the Chinese electricity mix in 2019 and the projection for future grid improvement are described in detail in Note 3 in SI.

Generally, the machine tools are delivered to dedicated companies for recycling in the EoL stage. Here, it was assumed that the materials, including steel, aluminum, and copper would be collected for recycling in the EoL stage. These collected materials can be used to produce secondary materials, thus avoiding the impact of the production of the primary materials. They were included in the emissions credit calculation. The emissions of the recovery of recycled materials were taken from the Ecoinvent v.3.5 dataset.

4. Results

Tables 3-5 show the yearly-distributed GHG emissions of the two machine tools under the scenarios S1, S2 and S3, respectively. It can be seen that the total amounts of GHG emissions in S2 and S3 are smaller than those in S1, due to the improvement of the electricity mix. The total aggregated GHG emissions in the conventional LCA are the same as the total amounts of GHG emissions in S1.

Fig. 4 shows the GWI of the two machine tools for producing one piece of gear under all the scenarios considered in this case study with a TH of 100 years. It can be seen from the figure that the life cycle GWIs of YDE and YS for producing one piece of gear are 41.7 and 61.9 gCO_2e in the conventional LCA, respectively. They correspondingly decrease to 37.5 and 55.3 gCO_2e, when the emission time and the dynamic aspects of the machine tools are considered in S3. The TGWP of S1 is reduced by 3% for the two machines compared with the BAU, since the CRF of GHG emissions occurring after the chosen TH are not calculated. If the electricity improvement is additionally considered, this reduction increases to 6% as shown in S2. Moreover, by further integrating the different machine tool use modes, the differences will increase to 10% and 11% for YDE and YS, respectively. Due to the fact that same amounts of GHG emissions during the machine tool operation stage produce less GWI than those in the CTG stage, the contribution of the manufacturing stage for both machine tools is increased when the dynamic LCA is applied. For all four scenarios, the YS performs worse than the YDE in GWI, mainly because it emits more GHGs during its use stage.

Fig. 5 shows the changes of TGWP of the machine tools with the production volumes under the four scenarios. At the beginning of machine tool use, i.e., when the production volume is zero, the two machines have constant emissions caused by machine manufacturing. Then, the impact increases with the increase of production volumes. In the BAU, the impact is increased linearly, while it grows more slowly with the increase of production volumes in S1, S2 and S3. This is because the impact of the GHG emissions gets lower over time in the dynamic LCA. In such a context, the same amounts of GHGs emitting later during the machine tool use have a lower impact than those occurring earlier. Although the YDE generates more GHG emissions than the YS in the machine manufacturing stage, it generates fewer emissions for producing one gear in the use stage. Thus, the YDE is inferior to the YS until the production volume exceeds the crossover point, as shown in Fig. 5. While when taking the temporal effect into account, the crossover production volume becomes larger. It means that more payback time is required to make the GWI of YDE lower than that of the YS in a dynamic assessment.

5. Discussions

5.1. Effect of TH on LCA results

Although the default TH of 100 years is exclusively used in the current GWI assessment, debates over analytical THs still exist. The above comparative results of static and dynamic LCAs of machine tools are obtained based on the default TH of 100 years. However, the application of various THs may have significant influences on the results, especially for the dynamic assessment. Thus, the effect of various THs on the GWI assessment of machine tools is further investigated. The S1 scenario is taken as an illustration to reveal the effect of THs on the relative differences between the static and the dynamic LCAs. Figs. 6 (a) and (b) show the changes of the GWI of YDE for producing one piece of gear with the extension of TH, in terms of TGWP and TCRF, respectively. Fig. 6 (b) shows that the TCRFs of the two machine tools under BAU and S1 scenarios are increased with the extension of TH; while the GWI of the static LCA shows an inverse trend with the variation of THs in term of TGWP, as shown in Fig. 6 (a). This is mainly because the growth of the denominator is faster than the numerator in the TGWP calculation. However, the differences between BAU and S1 scenarios are the same for the two different CFs, as shown in Figs 6. (a) and (b), respectively, both decreasing with the extension of TH. For example, at a 20-year TH, the overestimation of the static LCA reaches 14%, while at a 500-year TH, this difference is only 0.5%. The main reason for this is that the larger the TH is accounted for, the less radiative forcing is cut off. It means that the effect of emission time becomes less prominent when the TH is increased, because the service time of the machine tools is not that significant, compared with the longer THs. Thus, it is less important to account for emission time at longer analytical THs for the GWI assessment of machine tools.

5.2. Key points to incorporate time effect in GWI assessment of machine tools

The static LCA has the potential to overestimate the real GWI of machine tools. However, the extent to which the GWI is overestimated is case-specific and depends on the temporally distributed LCIs of machine tools and the selected THs. Under the current default TH of 100 years, it is decided by the temporally distributed LCIs. First, the longer the service life of the machine tools, the wider the distribution of GHG emissions over time. Hence, more impact of GHGs especially emitting around the end of machine use would be excluded from the GWI assessment in the dynamic LCA. It finally makes the differences between static and dynamic LCAs of machine tools larger. Thus, it is necessary to

incorporate the time effect in the GWI of machine tools, especially when the time period of emissions is long. Moreover, the use stage generally dominates the life cycle GHG emissions of machine tools. Thus, the technology development of the electricity grid over time would highly affect their GHG emissions. If more clean energy-based electricity is generated in the future, fewer GHGs will be emitted during the operation of machines. Therefore, considering the dynamic changes of LCIs due to the improvement of the electricity grid is also important to reflect the real emissions of machine tools and support decision making.

6. Conclusions

This paper conducts a dynamic GWI assessment of machine tools, considering the emission time and the potential dynamic changes of LCIs over time, due to the improvement of the electricity mix and the changes of machine use modes. TGWP and TCRF are applied separately to characterize the GWI. The gear hobbing machine YDE and its counterpart YS are used as a case to illustrate the dynamic LCA method and study the temporal effect on the LCA results. Three additional scenarios considering different dynamic factors are studied to compare the proposed dynamic LCA with the conventional static LCA. The results show that the two machines offer 3% reduction of GWI when emission time is considered. While a further 6% reduction is obtained if electricity improvement is additionally considered. Moreover, further reductions of 10% and 11% are obtained for YDE and YS, respectively, by considering different machine tool use modes. The YDE outperforms the YS in GWI in both static and dynamic assessments. However, more payback time is required for YDE to make its GWI lower than that of the YS in a dynamic assessment. With the extension of THs, the differences between the static and the dynamic assessments get smaller. Thus, it is more important to account for the emission time at shorter THs or for a longer lifetime of machine tools.

This work provides a method to dynamically assess the GWI of machine tools. The significant influence of dynamic factors on the machine tool LCA is revealed. The method applied in this work can also be used for the assessment of other types of products, like vehicles and buildings, etc., to capture their real GWI and further support robust decision-making. Notably, this work is an initial trial for the dynamic GWI assessment of machine tools. There are still some challenges in integrating the time effect into the GWI assessment of machine tools, including the acquisition of the accurate time frames of the machine tool life cycle, particularly the time scales for upstream production activities, and the corresponding LCI data. Furthermore, other dynamic impact categories need to be considered to provide a wider perspective on the life cycle environmental impact of machine tools. These will be the topics for future work.

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Tables

Table 1 The main technical parameters of the machine tools.

Parameters	YDE3120CNC	YS3118CNC5
Maximum machining diameter [mm]	210	180
Maximum machining module [mm]	4	4
Maximum rotate speed of spindle [r/min]	3000	1000
Maximum rotate speed of workbench [r/min]	300	200
Main motor power [kW]	22	7
Net weight [kg]	13000	9000
Cooling and lubricating	Dry	Coolant and lubricant oil
Design life time	10 years	10 years
Design shifts	Two	Two

Table 2 Four scenarios analyzed in this paper.

Scenarios	Considering emission time	Considering electricity mix improvement	Machine tool use modes
BAU[1]	No	No	Two shifts
S1	Yes	No	Two shifts
S2	Yes	Yes	Two shifts
S3	Yes	Yes	One shift

Note: [1]BAU denotes business as usual. It is the baseline, representing the conventional static LCA of machine tools.

Table 3 Temporally differentiated GHG emissions of the two machine tools in S1.

Phases	Year	YDE3120CNC			YS3118CNC5		
		CO_2 (kg)	CH_4 (kg)	N_2O (kg)	CO_2 (kg)	CH_4 (kg)	N_2O (kg)
Material extraction and machine tool manufacturing	2019	35429	21	0.65	24909	16.1	0.50
Use	2020	14268	1.7	0.22	12843	1.7	0.20
	2021	14268	1.7	0.22	12843	1.7	0.20
	2022	14268	1.7	0.22	12843	1.7	0.20
	2023	14268	1.7	0.22	12843	1.7	0.20
	2024	14268	1.7	0.22	12843	1.7	0.20
	2025	14268	1.7	0.22	12843	1.7	0.20
	2026	14268	1.7	0.22	12843	1.7	0.20
	2027	14268	1.7	0.22	12843	1.7	0.20
	2028	14268	1.7	0.22	12843	1.7	0.20
	2029	14268	1.7	0.22	12843	1.7	0.20
EoL	2030	-23679	-11	-0.33	-16480	-8.3	-0.25
Total	-	154426	27	2.56	136856	25.4	2.27

Table 4 Temporally differentiated GHG emissions of the two machine tools in S2.

Phases	Year	YDE3120CNC			YS3118CNC5		
		CO_2 (kg)	CH_4 (kg)	N_2O (kg)	CO_2 (kg)	CH_4 (kg)	N_2O (kg)
Material extraction and manufacturing	2019	35429	21.1	0.65	24909	16.1	0.50
Use	2020	14171	1.8	0.22	12756	1.9	0.20
	2021	14074	1.9	0.22	12670	2.0	0.20
	2022	13977	2.0	0.22	12583	2.1	0.20
	2023	13881	2.1	0.23	12497	2.2	0.20
	2024	13784	2.2	0.23	12411	2.3	0.20
	2025	13687	2.4	0.23	12324	2.4	0.20
	2026	13591	2.5	0.23	12237	2.6	0.20
	2027	13495	2.7	0.23	12151	2.7	0.20
	2028	13398	2.8	0.23	12065	2.8	0.21
	2029	13302	2.9	0.23	11978	2.9	0.21
EoL	2030	-23436	-11.4	-0.33	-16309	5.3	0.22
Total	-	149354	33.0	2.58	132272	45.3	2.76

Table 5 Temporally differentiated GHG emissions of the two machine tools in S3.

Phases	Year	YDE3120CNC			YS3118CNC5		
		CO_2 (kg)	CH_4 (kg)	N_2O (kg)	CO_2 (kg)	CH_4 (kg)	N_2O (kg)
Material extraction and manufacturing	2019	35429	21.1	0.65	24909	16.1	0.50
Use	2020	7086	0.9	0.11	6378	0.9	0.10
	2021	7037	0.9	0.11	6335	1.0	0.10
	2022	6989	1.0	0.11	6292	1.0	0.10
	2023	6941	1.1	0.11	6249	1.1	0.10
	2024	6892	1.1	0.11	6205	1.2	0.10
	2025	6844	1.2	0.11	6162	1.2	0.10
	2026	6795	1.2	0.11	6119	1.3	0.10
	2027	6747	1.3	0.11	6075	1.3	0.10
	2028	6699	1.4	0.11	6032	1.4	0.10
	2029	6651	1.5	0.11	5989	1.4	0.10
	2030	6603	1.5	0.11	5946	1.5	0.10
	2031	6571	1.6	0.11	5918	1.5	0.10
	2032	6540	1.6	0.11	5890	1.5	0.10
	2033	6512	1.6	0.11	5864	1.5	0.10
	2034	6483	1.6	0.11	5839	1.5	0.10
	2035	6455	1.6	0.11	5814	1.6	0.10
	2036	6427	1.6	0.11	5789	1.6	0.10
	2037	6399	1.6	0.11	5763	1.6	0.10
	2038	6371	1.6	0.11	5738	1.6	0.10
	2039	6342	1.6	0.11	5713	1.6	0.10
EoL	2040	-23293	-11.4	-0.33	-16208	-8.5	-0.25
Total	-	145519	37.2	2.59	128811	35.0	2.30

Figures

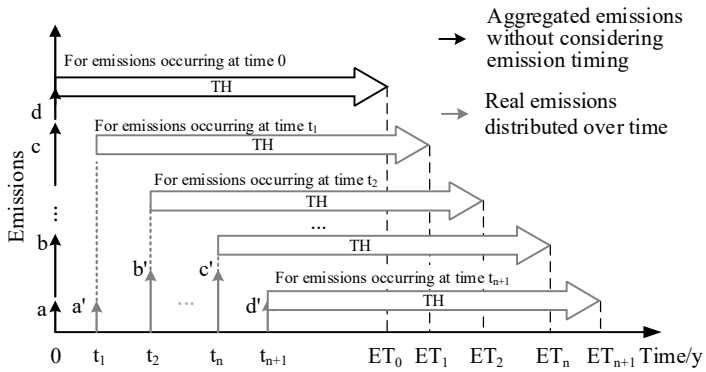

Fig.1 Illustration of the temporal inconsistency due to emission aggregation in the static GWI assessment, where t represents the time of GHGs emissions occurred and ET represents the reference time of the evaluation. It can be seen that the real GHG emissions of a machine tool are distributed over the life cycle, like a', b', c' and d'. In the static LCA, they are aggregated directly and using the same default TH of 100 years to calculate their GWI. This would lead to the inconsistent reference time of the evaluation.

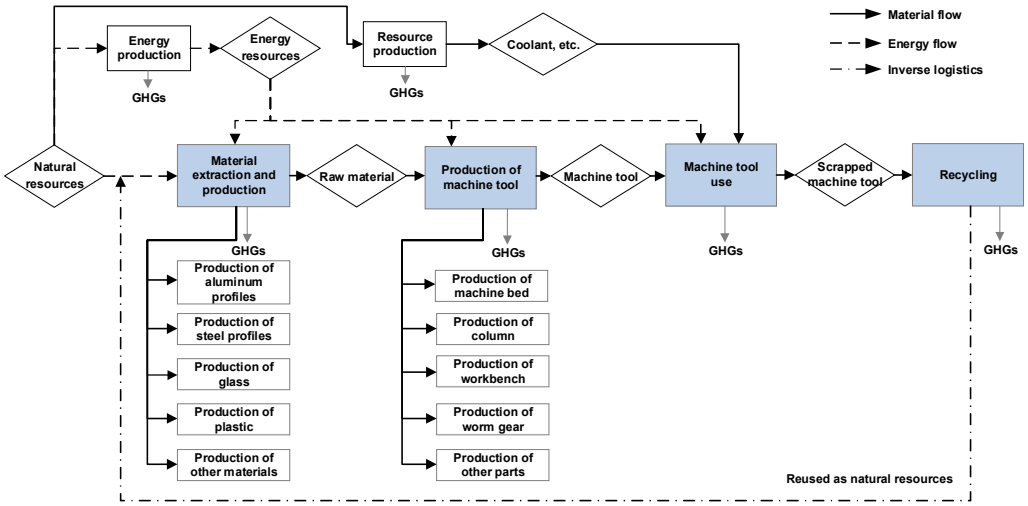

Fig. 2 System boundaries for life cycle GWI assessment of machine tools.

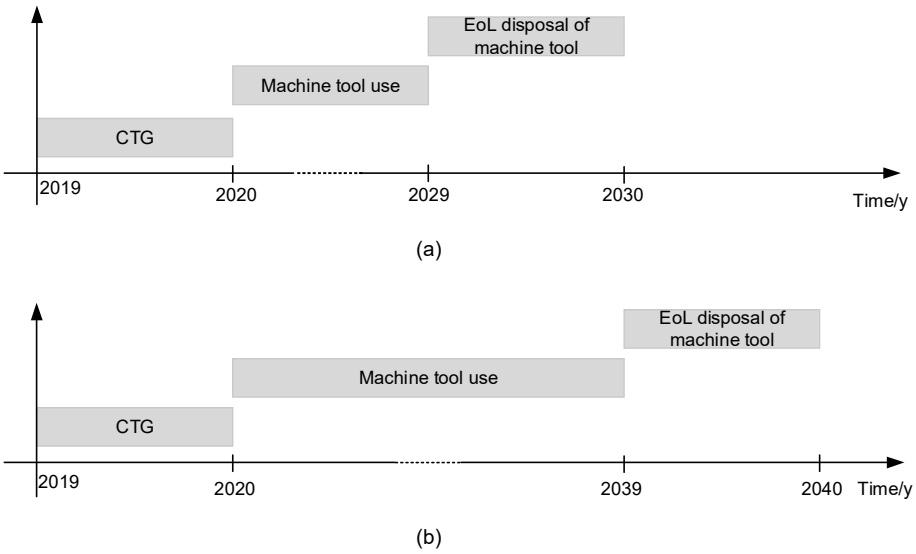

Fig.3 Time frames of the whole life cycles of the two machine tools, under the use scenarios of operating (a) two shifts and (b) one shift per day. The CTG represents cradle to gate and includes materials extraction, materials production, and machine tool manufacturing stages.

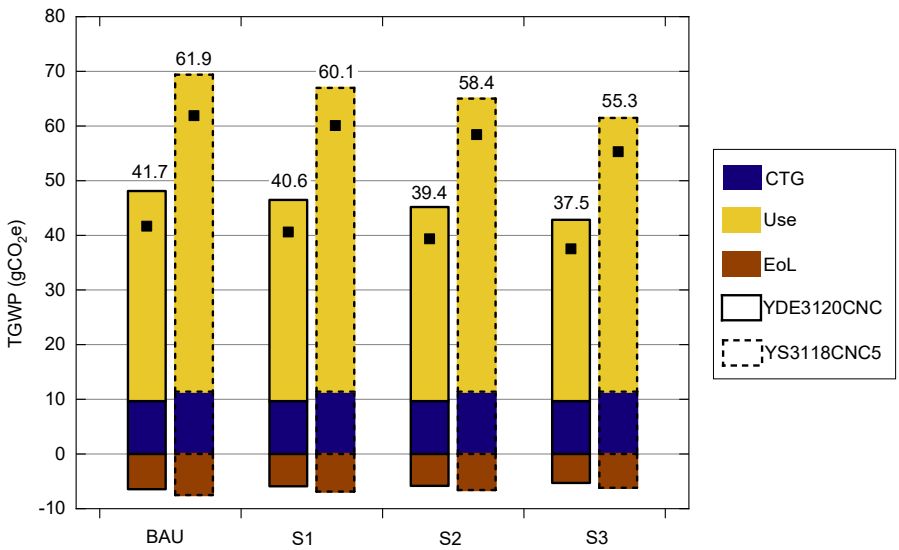

Fig.4 GWI of the two machines for producing one piece of gear under different scenarios. Black dots represent total impact by adding positive and negative impact contributions.

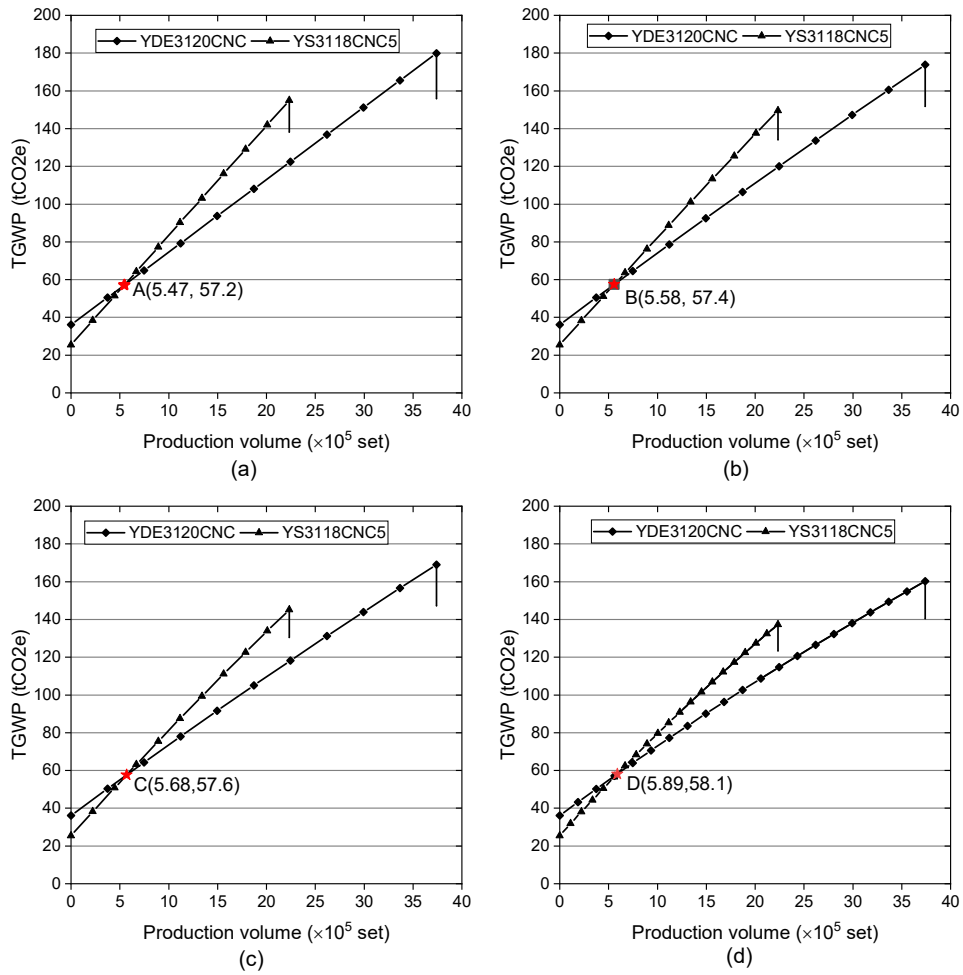

Fig. 5 The changes of TGWP of the two machine tools with production volumes under (a) BAU, (b) S1, (c) S2, and (d) S3. The red star represents the crossover point of the two machines.

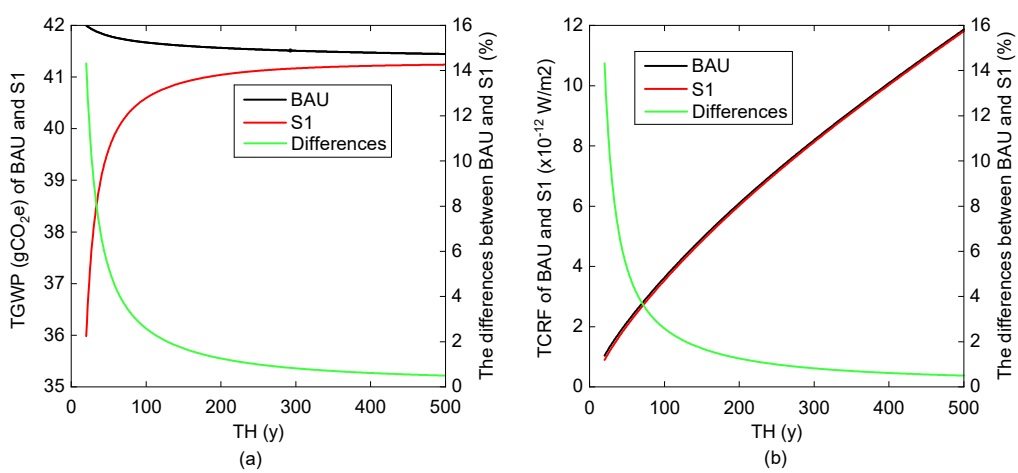

Fig. 6 The variations of differences between BAU and S1 over THs, in terms of (a) TGWP and (b) TCRF.