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Process-oriented Life Cycle Assessment framework for environmentally conscious manufacturing

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Abstract Environmental concern requires manufacturers to extend the domain of their control and responsibility across the product's life cycle. Much of the research has concentrated on assessment of environmental performance through the application of the Life Cycle Assessment (LCA) framework that provides a technical methodology to help identification of environmental impacts of product systems. However, the current LCA framework does not incorporate dynamic and diverse characteristics of manufacturing processes. As a result, the LCA's referential data will largely deviate from the real ones to an extent that the purpose of LCA is not meaningful. In other words, the current and fixed referential data-based method is not suitable to specify the impact categories related to manufacturing processes. From the perspective of decision making related with environmental impact during manufacturing, the current LCA method carried out in the off-line is hard to apply. As a result, performance index, such as greenability, a major performance index for environment conscious manufacturing cannot be implemented in the real practice. This paper presents the development of a framework (called process-oriented LCA) to realize environmental conscious manufacturing incorporating both greenability and productivity. To show the applicability and validity of this framework, experiments and analysis have been conducted and a prototype system has been implemented for a turning machining process.

Keywords Life Cycle Assessment · Environmentally conscious manufacturing · Energy efficiency · Green productivity · Greenability

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Introduction

Environmental issues have been drawing attention worldwide by governmental regulations and customer perspectives (Gungor and Gupta 1999). These issues naturally call for consumer's more attention to product information and environmentally-friendly products with clean production processes (Le and Lee 2013). This attention demands for manufacturers to extend their domain of control and responsibility across the product's life cycle including Begin-of-Life (BOL: design and manufacturing), Middle-of-Life (MOL: use and maintenance) and End-of-Life (EOL: recycling and disposal) (Suh et al. 2008). Much of relevant efforts have focused on assessment of the environmental impacts of the product's life cycle through the application of the Life Cycle Assessment (LCA) framework (Rebitzer et al. 2004).

The LCA framework provides a technical methodology that helps identify explicit and implicit environmental impacts of product systems (ISO 2006). The phases

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of the LCA framework consist of goal and scope definition, Life Cycle Inventory analysis (LCI), Life Cycle Impact Assessment (LCIA) and interpretation. Specifically, the LCI involves data collection and procedures to quantify relevant inputs and outputs of a product system, while the LCIA evaluates the significance of potential environmental impacts by using the LCI results (ISO 2006).

However, the application of the LCA framework to the manufacturing stage has some limitations to obtain accurate and reliable results. In the LCI phase, the referential data provided by LCA's supporting tools have been commonly used. These referential data do not much coincide with the real data measured from manufacturing processes (Frischknecht et al. 2007). In addition, environmental performance assessment is based only on the amount of material processed, while production rate, manufacturing options (e.g., wet, dry or minimum quantity lubricants) and the fixed resource consumption due to operations of peripheral equipment are neglected (Duflou et al. 2011; Jiang et al. 2012). In the LCIA phase, an impact assessment method from LCIA guidelines such as CML 2002 (Guinee et al. 2001), Eco-Indicator 99 (Goedkoop and Spriensma 2001) and ReCiPe (Goedkoop et al. 2013) can be chosen. They can differ in the impact categories and weighting factors they cover by their selection of indicators and by their country and geographical focus. Because an LCIA method is appropriately assigned in terms of the product and its surrounding circumstances (Lehtinen et al. 2011), this LCIA method is not suitable to specify the impact categories related to manufacturing processes.

Moreover, the application of the LCA framework has been executed outside the shop floor that can dynamically and unexpectedly change their operational flows and/or control parameters. It is not easy to use the results derived from the application of this framework for making timely decisions (i.e., decisions made within allowable time span) in the shop floor. Also, diagnosis, prediction and optimization that are not included in the LCA framework can contribute to improvements in environmental performance.

On the other hand, the fundamental objective of manufacturing processes is to produce goods with higher productivity that pursues increase in speed, cost and quality performances. This nature of manufacturing processes inevitably requires productivity-biased process improvement rather than improvement in environmental performance. In other words, greenability or environmental friendliness is not considered to be a major performance indicator in manufacturing processes (Krause et al. 2012).

This paper presents the development of a framework, called process-oriented LCA framework, for the implementation of environmentally conscious manufacturing paradigm, hereafter eco-manufacturing. The framework identifies a systematic and structural method to: (1) support process-oriented decision-making in shop floors on the basis of the manufacturing data measured from manufacturing processes and (2) assess, diagnose, predict and optimize environmental performance in manufacturing processes. The core mechanisms of this framework are the realization of the process improvement cycle and the integration of the LCA framework with categorical quantification of performance indicators. To show the applicability and validity of this framework, this framework has been implemented into a machining process. An experiment has been conducted and a prototype system has been developed with a turning machining process. The deliverable of this paper can contribute to provide a technical solution that can harmonizes enhanced greenability performance with improved productivity performance, called Green Productivity (GP) (APO 2006).

"Literature review" section of this paper reviews the relevant literature, and "Design consideration" section clarifies the design considerations necessary for the development of the process-oriented LCA framework. "Process-oriented LCA framework" section introduces this framework, and "Application of process-oriented LCA framework" section explains its application method. "Implementation" section presents a process planning model as a practical application of the framework. "Experiment and prototype development" section describes an experimental approach and a prototype development with discussions. "Conclusion" section offers a summary and conclusions for our work.

Literature review

Because greenability, as mentioned in "Introduction" section, is not considered to be a major performance indicator in manufacturing processes, some manufacturers have been unfamiliar with the implementation of the eco-manufacturing paradigm. To support easy and systematic implementation of this paradigm into their manufacturing processes, some researches have been strived to develop the methods that can integrate the LCA framework with manufacturing processes. Other researches have been performed to develop new frameworks and methodologies that identify tactics, actions and procedures for assessment and improvement of environmental performance in manufacturing domain. This section addresses the researches relevant to development of prior frameworks and methodologies in manufacturing domain. This section then identifies current limitations in the researches of this area.

The CO2PE! Initiative (Kellens et al. 2012) and Ecoinvent (Frischknecht et al. 2007) have contributed to the development of structural frameworks and inventories of unified and generic LCI data for unit-manufacturing processes. These efforts open up the possibility to many industrial groups of using high quality LCI inventories. However, these LCI inventories cannot cover all diverse and dynamic characteristics of manufacturing processes because these inventories have their boundary and thus only provide referential LCI data for unit-manufacturing processes. For example, Eco-invent provides a referential data set that encompasses material removed, energy consumption, compressed air and lubricant oil for 1kg-aluminium material removal in a turning machining process (Frischknecht et al. 2007). This data set helps industrial groups understand and analyze environmental impacts affected by turning machining. The current version of this data set needs to be transformed and adjusted for other materials' removal, thereby requiring additional works for its use in other material cases.

Several works have contributed to provide technical methodologies to undertake assessment of environmental performance for manufacturing processes and systems. Jiang et al. (2012) presented a method for the environmental evaluation of a machining process plan by forming an impact matrix of environmental measures. Bonvoisin et al. (2013) proposed a conceptual framework to assess energy consumption of machining processes by the use of a simulation technique from a product design perspective. Winter et al. (2013) suggested a stepwise approach to compare tools, cutting fluids and machine tools in conjunction with process parameters to reduce costs and environmental impacts of a grinding process. Mélanie et al. (2013) developed a tactics library to provide a connection between concepts and operational practices for resource efficiency in a factory. Li et al. (2013) proposed an analytical methodology to quantify carbon emissions of a Computerized Numerical Control (CNC) system including electricity, cutting fluid, wear of cutting tools and disposal of chips. Jia et al. (2014a) introduced a modeling methodology that links activities, machining states and the basic energy unit for energy calculation in a machining process. Jia et al. (2014b) also applied the methodology to analyze the energy consumed by the execution of a Numerical Control (NC) program. Other works have suggested methodologies useful for improving environmental performances in manufacturing. Iqbal et al. (2013) presented a fuzzy rule-based methodology for minimizing energy consumption, maximizing tool life and Material Removal Rate (MRR). Shao et al. (2014) proposed a step-by-step guidance to optimize sustainability performance using Sustainable Process Analytics Formalism that enables manufacturers to generate an application-neutral model for representing manufacturing processes, control variables, and analytical models of metrics and constraints. Peng and Xu (2014) proposed the framework of the global energy-efficient machining system to function energy metering, analysis and optimization with consideration of data interoperability in the computer-aided process chain.

The literature reviews show that so far no efforts have been made toward implementation of a process-oriented environment that enables manufacturers to make timely decisions on their environmental performances through manufacturing data collected from their shop floor operations. Additionally, no efforts have been made to develop comprehensive methodologies that encompass assessment, diagnosis, prediction and optimization for improvement of the environmental performances with consideration of productivity performances. The present work was motivated by the need to develop a process-oriented and comprehensive framework for improving multiple productivity and greenability performances, which can customize the existing LCA framework for the application to manufacturing processes and systems.

Design consideration

To overcome the current limitations described in "Literature review" section, it is necessary to develop a framework that can assure a process-oriented decision-making environment based on the data collected from manufacturing processes. It is also vital to conceive an efficient integration of environment-oriented methodologies with manufacturing-oriented methodologies. For such a purpose, the proven techniques of the LCA framework from the environmental domain are utilized to provide quantitative and effective assessment of environmental performance. The traditional and commonly-used concept of Define-Measure-Analyze-Improve-Control (DMAIC) cycle (Kuei and Madu 2003) is also adapted to increase productivity and greenability in manufacturing processes.

In particular, a single index, called the Green Productivity Index (GPI), is designed to represent the integrated productivity and greenability performance of manufacturing processes. The use of this single index can support fast decision-making for manufacturing processes. Additionally, the data-intensive decision environment needs to be considered to assess, diagnose, predict and optimize environmental performance accurately and reliably in manufacturing processes. Our framework takes the following design factors into consideration:

(1) On-line data collection and processing: data collection and processing are complicated procedures in manufacturing processes. The elements of a shop floor, i.e., humans, machines and materials, create a huge amount of data. Moreover, there is no assurance of conformance and reliability of data; the data may be erroneous, noisy or missing. In this context, it is important to supply, in a timely fashion, clean and reliable manufacturing data necessary to make the right decisions for the improvement of the GP performance. Therefore, it is important to consider on-line data collection and processing methods to efficiently supply the necessary manufacturing data.
(2) Utilization of LCA techniques: LCA techniques are effective even in manufacturing processes because they

are proven and further improved by a number of environmental experts. LCA techniques (e.g., allocation, characterization, categorization, weighting and sensitivity analysis) should be adopted to measure and assess environmental performance in the manufacturing domain because of the current unavailability of any such techniques.

(3) Adaption of the DMAIC cycle: a continuous process improvement cycle needs to be implemented in a new framework to provide the feedback necessary for improvement of GP performance. It is fundamental to measure relevant data and then to assess the GP from this data. Furthermore, diagnosis, prediction and optimization can be incorporated to enhance the GP through specification of planning and control parameters that can be fed forward to the manufacturing processes. Therefore, it is necessary to implement a measure-assess-diagnose-predict-optimize-control mechanism by adapting the DMAIC cycle approach to provide the structural phases necessary to ensure continuous process improvement.

(4) Integration of productivity and greenability performance: it is difficult to quantify several of performance categories due to the complex interrelationship between their criteria (Tangen 2004). Nevertheless, it is significant to integrate and balance productivity-related performance criteria with greenability-related performance criteria. The integration of these two heterogeneous sets of criteria is currently beyond the capability of the LCA framework, which only incorporates environmental performance. Therefore, a new framework needs the design of subordinate performance categories that can be used to calculate the two heterogeneous performance criteria. In turn, a single index needs to be designed to combine these two criteria.

(5) Technical extension toward diagnosis, prediction and optimization: the LCA framework and the DMAIC cycle do not incorporate the technical methodology required for diagnosis, prediction and optimization, which are necessary for the improvement of the GP performance. For example, many LCA guidelines rely only on human-intensive decisions to find solutions for the improvement of environmental performance, whereas data-intensive decisions provide more accurate and reliable solutions. Therefore, a new framework needs to provide statistical, empirical and machine-learning techniques to technically support data-intensive decisions for the improvement of the GP performance.

Process-oriented LCA framework

Based on the design factors described in “Design consideration” section, a process-oriented LCA framework has been developed, as a technical solution, to provide a structure and method to enhance the GP performance for manufacturing processes. This framework consists of two models: a conceptual model to define layers to compose the structure of the framework, and a procedural model to specify how to apply the framework into manufacturing processes. “Conceptual model” and “Procedural model” sections, respectively, introduce the conceptual model and the procedural model.

Conceptual model

It is a primary work to specify the allocation of the functions adapted from the DMAIC cycle that executes the process-oriented LCA framework. Figure 1 presents the conceptual model that identifies the allocation of these functions into a structure to consist of the six layers—production, data acquisition and refinement, process instantiation, assessment, analytics and feedback.

The ‘production’ layer indicates a manufacturing system where real manufacturing processes occur. ‘Data acquisition and refinement’ collects, refines and stores manufacturing data. The manufacturing data can be categorized as the tangible inputs and outputs of resources or the process properties (i.e., intangible process metrics such as work-in-process time, machine availability and surface quality). ‘Process instantiation’ instantiates the manufacturing data into a predefined process model to capture a snap shot of a manufacturing system. ‘Assessment’ evaluates the GPI and its subordinate performance criteria of the instantiated process model. ‘Analytics’ carries out diagnosis, prediction and optimization to make feasible solutions that include process planning decisions and control parameters. ‘Feedback’ feeds the planning decisions and control parameters forward to the manufacturing system. The circulated and continuous execution of these layers can deliver the best feasible solutions to the manufacturing system.

Procedural model

Similar to the application of the LCA framework, the application of the process-oriented LCA framework into a manufacturing system is not easy because it is technically complex. Thus, another primary work is to specify how to apply this framework to consolidate its efficient and reliable applications.

Figure 2 visualizes the procedural model that identifies the application of the process-oriented LCA framework. The procedure consists of the ten steps categorized into three phases. The ‘off-line’ phase indicates the preliminary modeling stage for real data acquisition and assessment. ‘On-line’ means the collection of the relevant data from real shop floor operations and the assessment of the GPI and its subordinate performance indexes. ‘Post-line’ relates to the execution of

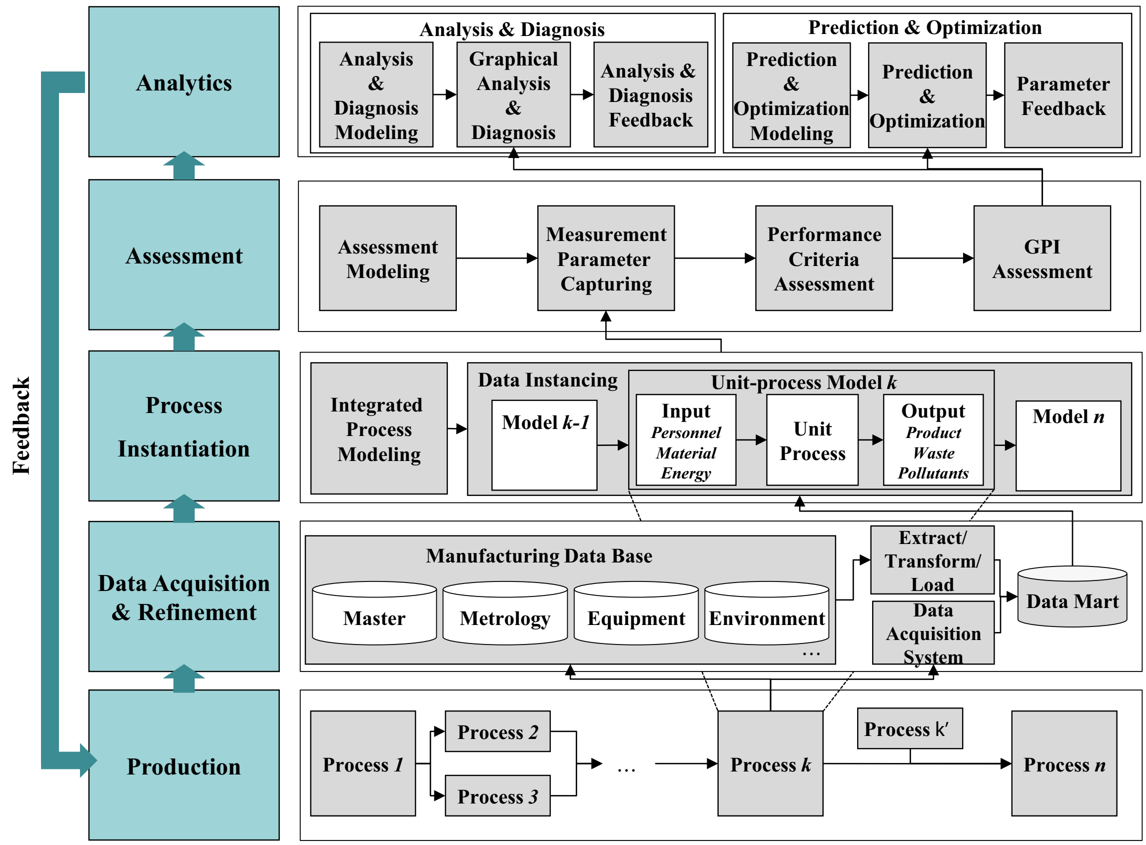


Fig. 1 A conceptual model of the process-oriented LCA framework

the analytics and the feedback corresponding to the 'analytics' layer and the 'feedback' layer in Fig. 1. The details of these steps are described in the following section.

Application of process-oriented LCA framework

As mentioned above, "Application of process-oriented LCA framework" section describes the technical details for each step of the efficient and reliable application of the process-oriented LCA framework. Specifically, we propose a well-defined procedure that includes: (1) how to define a problem, (2) how to derive solutions for the problem, and (3) how to generate strategies for improving GP performance.

Goal and scope definition

The purpose of this step is to define an objective function to measure and improve the performance of the target manufacturing system. To do this, it might be necessary to identify a system boundary within the manufacturing system which excludes those parts of the manufacturing system unnecessary or irrelevant to the analysis of performance. The lack or complexity of data for the manufacturing system can make the determination of this system boundary difficult. Because certain assumptions and constraints can be made to achieve these goals, the current step should be revisited after the specification of each subsequent step in order to check for compatibility with an objective function and an identified system boundary.

Manufacturing process modeling

An objective of this step is to create a manufacturing process model that integrates a collection of unit-manufacturing processes, inputs, outputs and facilities. Figure 3 shows an example of the manufacturing process model that specifies manufacturing processes, facilities and their associated materials and energy flows. Similar to the LCA framework, another objective of this step is to identify 'function' for defining the role of a manufacturing system and 'functional-unit' for defining a basic unit of a manufactured product.

As shown in Fig. 3, when a manufacturing system involves a multi-output process, a multi-input process or an open-loop recycling process, this process modeling work can utilize allocation techniques such as mass-based substitution or allocation, which are used for the allocation in the LCA framework (ISO 2006). In some cases, certain processes or

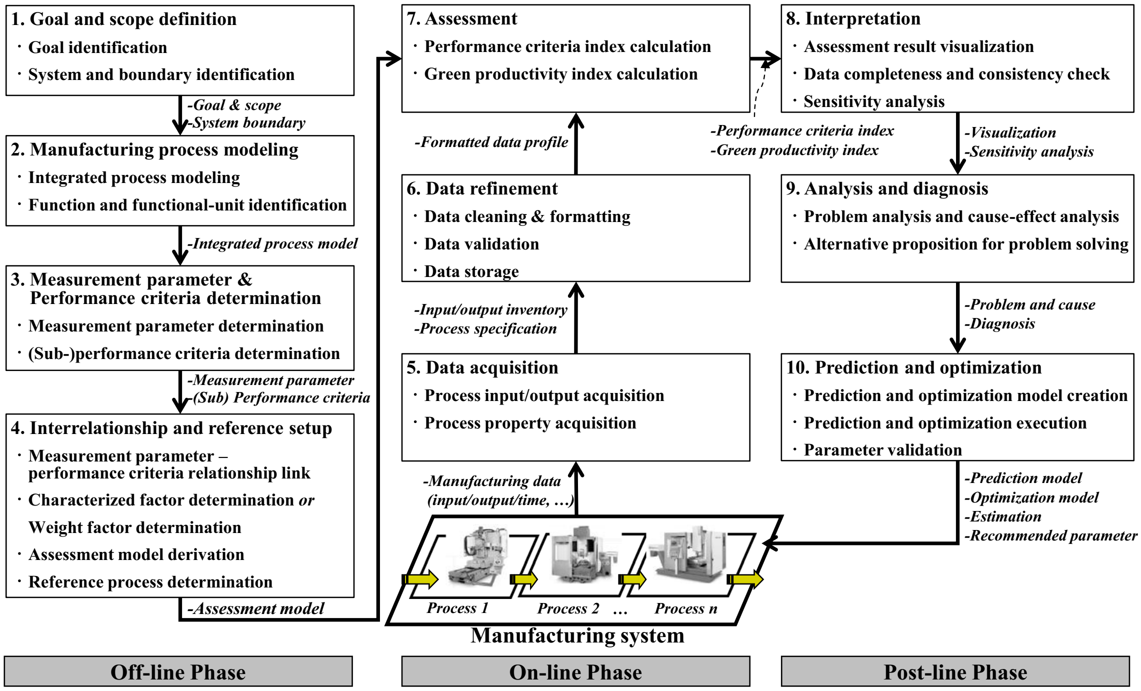


Fig. 2 A procedural model of the process-oriented LCA framework

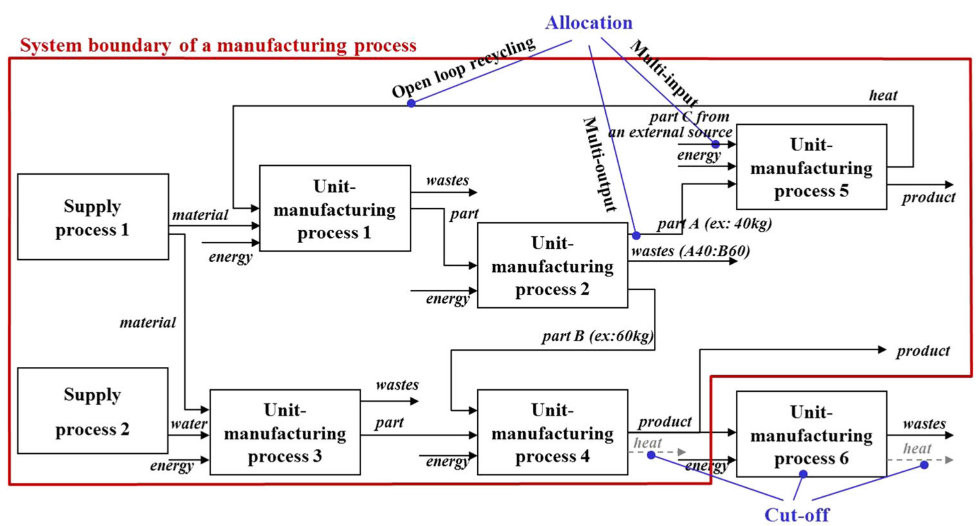


Fig. 3 An example of a manufacturing process model

data flows may be irrelevant and therefore excluded from the system boundary, as indicated by the red solid line in Fig. 3.

Measurement parameter and performance criteria determination

This step determines measurement parameters and their associated performance criteria. The measurement parameters can be defined as the metrics for process properties or inputs and outputs of material and energy flows that influence performance criteria within a manufacturing process. The performance criteria are defined as the performance categories to represent the impacts of the measurement parameters on the GP performance. Subordinate performance criteria may be necessary for in-depth analysis of the primary performance criteria.

Measurement parameters need to be measurable, calculable and explicit because they will be used to quantify performance criteria. The performance criteria should be named with the use of recognizable, reasonable and representative key words for common understanding of stakeholders.

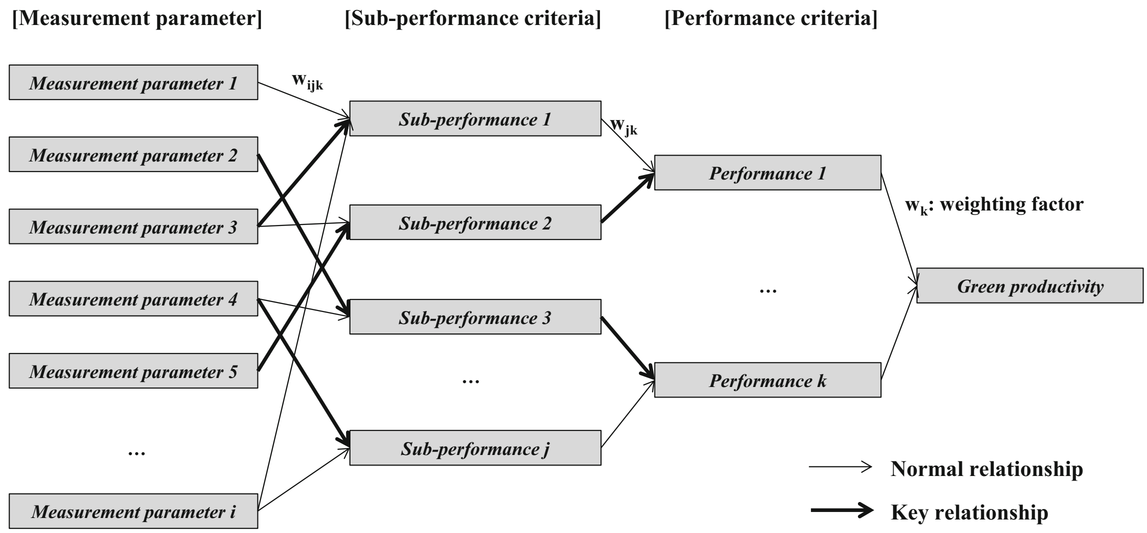


Fig. 4 An example of a relationship tree

Interrelationship and reference setup

This step inter-relates measurement parameters with performance criteria. This interrelationship should consider multiple connections because measurement parameters can influence several performance criteria.

There are two possible methods to pose the interrelationship. A characterized method characterizes the interrelationship between measurement parameters and performance criteria, as illustrated in Eq. (1). Here the characterized method calculates Performance Criteria Indexes (PCIs) by means of characterized factors that represent the equivalent influence of measurement parameters on a performance criterion. This concept of the characterized factor is similar to the Environmental Load Unit (ELU/kg) of Eco-indicator 99 (Goedkoop and Spriensma 2001).

$$\begin{aligned}
&1.\ Calculate\ sub-PCI(C_j)\\
&\quad C_j = \sum_{i=1} m_i \cdot \alpha_i\\
&2.\ Calculate\ PCI\ (C_k)\\
&\quad C_k = \sum_{j=1} C_j \cdot \beta_j\\
&3.\ Calculate\ GPI\\
&\quad GPI = \sum_{k=1} C_k \cdot \gamma_k
\end{aligned} \tag{1}$$

where, m_i a measurement parameter, α_i a characterized factor for sub-PCI, β_j a characterized factor for PCI, and γ_k a characterized factor for GPI.

Alternatively, a relative method can be used to calculate PCIs by the relative comparison between a reference manufacturing process and a current manufacturing process. As shown in Eq. (2), this method calculates the ratios of the measurement parameter values of these two processes. It then calculates a PCI by aggregating the products of the ratio multiplied by weighting factors. The use of the relative method requires the determination of weighting factors and the availability of a reference manufacturing process. Stakeholders can determine the weighting factors that quantify the relative impacts of measurement parameters on performance criteria. Figure 4 shows an example of a relationship tree that defines interrelationships and weighting factors. Sensitivity analysis or uncertainty analysis will be necessary in the 'interpretation' step ("Interpretation" section) because this relative method determines weighting factors subjectively. Finally, measurement parameters for the reference manufacturing process will be assigned reference values, and the GPI and PCIs for the reference process will each accordingly be assigned the referential value such as 1.0 to create a model to assess the GPI and PCIs for the current manufacturing process.

$$\begin{aligned}
&1.\ Calculate\ sub-PCI(C_j)\\
&\quad C_j = \sum_{i=1} w_{ijk} \cdot \frac{m_i, reference}{m_i, current}\\
&2.\ Calculate\ PCI(C_k)\\
&\quad C_k = \sum_{j=1} w_{jk} \cdot C_j\\
&3.\ Calculate\ GPI\\
&\quad GPI = \sum_{k=1} w_k \cdot C_k
\end{aligned} \tag{2}$$

where, $m_{i,reference}$ a measurement parameter for a reference manufacturing process, $m_{i,current}$ a measurement parameter for a current manufacturing process, w weighting factor, $\sum w_{ijk} = 1$, $\sum w_{jk} = 1$, and $\sum w_k = 1$.

Data acquisition

In this step, the manufacturing data relevant to measurement parameters from a manufacturing process are acquired. The

Table 1 An example of data acquisition options for a machining system

Measurement parameter	Acquisition method	Measurement device
Machining time	Manual: measure a time with stop watch	–
	Automatic: record a cycle start time and end time in a CNC	CNC
Roughness	Off-line: measure roughness using a handy measurement device	Roughness meter
	On-line: measure roughness using an on-line touch probe	Touch probe
Tool wear	Theoretical: use a tool wear equation	–
	Practical: measure tool wear using light interferometer, machine vision and so on	Light interferometer Machine vision
Power consumption	Theoretical: use a cutting power equation	–
	Virtual: use a virtual machining model	–
	Practical: measure an electronic power using an energy meter connected with power supply unit	Energy meter
Coolant loss	Manual: measure exposed coolant and recovered coolant, then subtract exposed coolant to recovered one	–
	Automatic: (1) measure missing coolant using aerosol monitor, (2) measure flow rates of coolant at nozzle and recovered tank	Aerosol sensor Flow rate sensor

manufacturing data are the fundamental assets necessary to assess, diagnose, predict and optimize the GPI and PCIs. This will be described in the following subsections.

To acquire the data, an equipment communication interface will transmit the manufacturing data from equipment to a data repository through messaging or file transfer protocols. When some measurement parameters are determined to be unavailable, the system boundary can be modified as discussed in "Goal and scope definition" section. Alternatively, theoretical and virtual models can be applied in the case of lack of equipment communication interfaces. Table 1 presents an example of data acquisition options for a machining system. For instance, there are three possible options in acquiring power consumption: the measurement by use of a theoretical cutting mechanism, the measurement by a virtual machining model and the measurement by the installation of an energy meter in a machine tool.

Data refinement

This step refines the manufacturing data and transforms them into a pre-defined data structure for extracting values of the measurement parameters. This step requires the functions of cleaning, formatting, validation and storage of the data, so called data pre-processing. Cleaning is for omitting unnecessary, erroneous and duplicated data. Formatting is for transforming the manufacturing data into a predefined data structure. Validation is for checking data reliability or uncertainty. Storage is for storing the formatted data in the repository. The output of these functions should assure the accuracy, integrity and consistency of the data. The data structure needs to be well designed because the data structure facilitates storage and retrieval of data.

Assessment

This step calculates the GPI and PCIs for the current manufacturing process by using the measurement parameters acquired. One of the two methods described in "Interrelationship and reference setup" section is chosen to calculate the GPI and PCIs. Stakeholders determine the time interval for the execution of this assessment. A constant periodic interval will be favorable for continuous manufacturing processes. An event-driven interval, marked by the occurrence of an event such as producing a functional-unit, will be favorable for discrete part manufacturing processes.

Interpretation

This step interprets and visualizes a result derived by the assessment and checks the reliability of the result. Visualization can be accomplished by graphical representations, such as a portfolio and a spider web diagram (Hur et al. 2004). For example, Fig. 5 illustrates a GPI portfolio that represents strength and weakness of the current manufacturing process in terms of greenability and productivity performances.

The reliability of the assessment can be checked using techniques from the interpretation step of the LCA phases. The data completeness check examines the availability and completeness of the data. The data consistency examines the consistency of assumptions, methods, and data. The sensitivity analysis evaluates the impact of the reliability of the

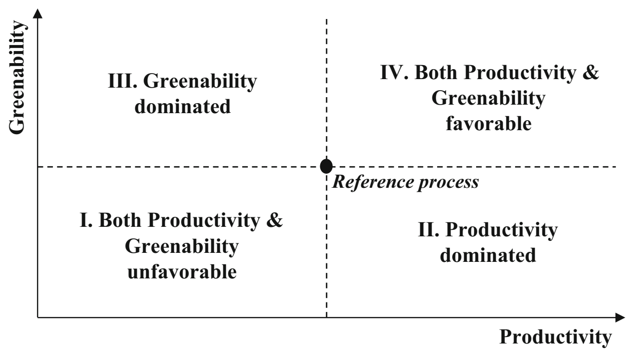


Fig. 5 A portfolio of GPI

assessment result due to uncertainties in the data, allocation methods and weighting factors (ISO 2000).

Analysis and diagnosis

This step analyzes and builds cause-and-effect relationships between planning and control parameters, measurement parameters, and the GPI and PCIs. When a PCI of the current manufacturing process is lower than that of the reference manufacturing process, the causal relationships can be made to trace back and diagnose the influences of the planning and control parameters. While the use of supporting tools and techniques can be beneficial to deliver reasonable diagnosis results, stakeholders will make their own final decisions based on their intensive knowledge.

Prediction and optimization

This step predicts the impacts of the choice of planning and control parameters on the GPI and PCIs. It can also determine the parameter set that optimizes the objective function defined in "Goal and scope definition" section. This step requires the design and validation of prediction and optimization models. The prediction model can build upon the cause and effect relationship analyzed in the last step to forecast the impact of changing the planning and control parameters. The optimization model will optimize the objective function and therefore improve the performance of the current manufacturing process.

Implementation

The proposed framework has been implemented into a real machining system to demonstrate its practical application. This section describes the development of a process planning model, hereafter GP planning model, by following the procedural model and its application method explained in "Process-oriented LCA framework" and "Application of process-oriented LCA framework" sections. The current section concentrates on the creation of an assessment model, a diagnosis model, a prediction model and an optimization model as the core logics of this GP planning model.

Goal and scope definition

The goal of the application of the process-oriented LCA framework is to develop a process planning model that enables the assessment, the diagnosis and the prediction of the GPI and the determination of process parameters for optimizing the GPI within the boundary of a machining process. Therefore, the objective functions can be set to assess, diagnose, predict and maximize the GPI.

Machining process modeling

Figure 6 provides a visualization of the process model that defines functions, inputs, outputs and controls of a machining

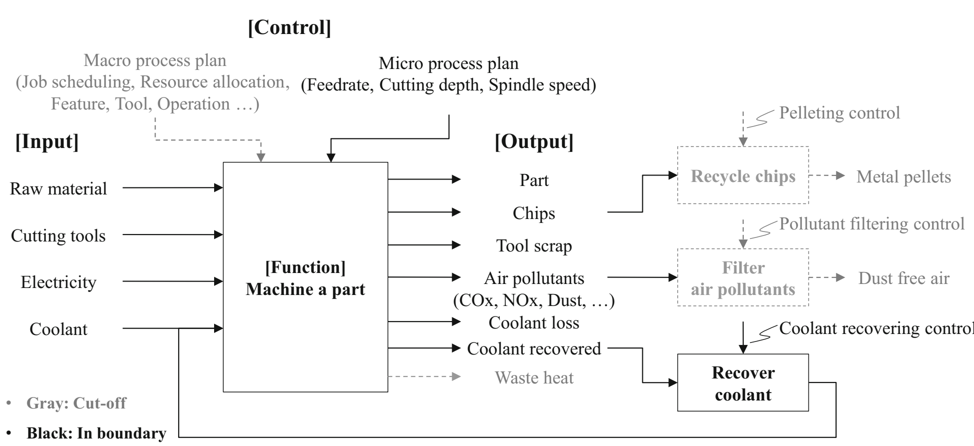


Fig. 6 A boundary of a machining process

process. ‘Function’ can be defined as ‘machine a part’, and ‘functional-unit’ as ‘a part machined by an NC part program’.

In this paper, the machining process involves the functions of ‘machine a part’ and ‘recover coolant’ while it excludes the functions of ‘recycle chips’ and ‘filter air pollutants’. The inputs to the function include ‘raw material’, ‘cutting tool’, ‘electricity’ and ‘coolant’. The outputs from the function include ‘part’, ‘chips’, ‘tool scrap’, ‘air pollutants’, ‘coolant loss’ and ‘coolant recovered’. The controls for the function include only main process parameters—‘feedrate’, ‘cutting depth’ and ‘spindle speed’.

Measurement parameter and performance criteria determination

‘Electricity’, ‘chip’, ‘tool scrap’, ‘air pollutant’ and ‘coolant loss’ are chosen as measurement parameters from the inputs and outputs of the in-boundary system shown in Fig. 6. In addition, ‘machining time’, ‘roughness’ and ‘tool use time’ are chosen as measurement parameters from the process properties of the machining system. ‘Electricity’ is re-defined as ‘power consumption’ obtained from the average power consumed during machining time. These measurement parameters will be more specified in Table 4.

Four machining experts participated in the determination of performance criteria. Productivity incorporates the two characteristics: (1) machining efficiency (i.e., the ease of machining with quality satisfaction), and (2) production efficiency (the quickness of machining). Greenability contains the three characteristics: (1) resource efficiency (quantity of material, tool and coolant used), (2) energy efficiency (quantity of energy consumed), and (3) anti-toxicity (quantity of toxic substances emitted). The term ‘efficiency’ means the comparative ratio between the current machining process and the reference machining process.

Interrelationship

The measurement parameters are inter-related to the performance criteria by using the relative method described in Eq. (2). The experts scored weighting factors on a 0-to-1 scale between the measurement parameters and the sub-performance criteria, as shown in Fig. 7a. They assigned the weighting factors between the sub-performance criteria and the performance criteria with the assumption that greenability is more important than productivity, and thus they imposed larger weights to greenability than to productivity, as shown in Fig. 7b. It is worth mentioning that these weighting factors assigned in this paper are not unconditional numbers. The weighting factors need to be well arranged with consideration of the target manufacturing process, performance criteria and measurement parameters.

(a)

Measurement parameter \ Sub performance criteria	Machining efficiency	Production efficiency	Resource efficiency	Energy efficiency	Anti-toxicity	Total
Machining time	0.066	**0.297**	0.099	0.167	0.134	-
Power consumption	0.085	0.055	0.118	**0.253**	0.010	-
Air pollutants	0.028	0.031	0.072	0.080	**0.309**	-
Roughness	**0.264**	0.172	0.026	0.047	0.0	-
Tool use time	**0.226**	0.117	0.164	0.087	0.052	-
Tool wear	**0.226**	0.094	0.171	0.113	0.093	-
Coolant loss	0.066	0.141	0.158	0.140	**0.320**	-
Chip mass	0.038	0.094	0.191	0.113	0.082	-
Total	1.000	1.000	1.000	1.000	1.000	5.000

(b)

Sub performance criteria \ Performance criteria	Productivity	Greenability	Green productivity
Machining efficiency	0.700		**0.300**
Production efficiency	0.300		
Resource efficiency		0.300	**0.700**
Energy efficiency		0.400	
Anti-toxicity		0.300	
Total	**1.000**	**1.000**	**1.000**

Fig. 7 A matrix of weighting factors between measurement parameters and (sub-) performance criteria. **a** Measurement parameter–sub performance criteria. **b** Sub performance criteria–performance criteria

Assessment modeling

Equation (3) describes the pseudocode to represent the assessment model that has been created from the execution of the procedure described in “Goal and scope definition”, “Machining process modeling”, “Measurement parameter and performance criteria determination” and “Interrelationship” sections. A measurement parameter of the current machining process is taken as the denominator and that of the reference machining process as the numerator because a lower measurement parameter of the current process implies a better performance than that of the reference process.

Step 1. *Initialization*
  1. *Set process plan parameter* $P(p_1, p_2, \ldots, p_l)$
  2. *Set measurement parameter* $M(m_1, m_2, \ldots, m_i)$
  3. *Link relationship between measurement parameter* (M)*and sub-performance criteria index* (C_j)
  4. *Link relationship between* C_j *and performance criteria index*(C_k)
  5. *Set weight factor* w_{ijk}, w_{jk}, w_k
  6. *Go to Step* 2
Step 2. *Reference condition setup*
  1. *Set reference process plan parameter to* P_{REF}
  2. *Read reference measurement parameter* (M_{REF}) *at* P_{REF}
  3. *Record* (P_{REF}, M_{REF}), *then set green productivity index (GPI)* $= 1.000$
  4. *Go to Step 3*
Step 3. *Current condition setup* (3)
  1. *Set current process parameter to* P_{CUR}
  2. *Read current measurement parameter* (M_{CUR}) *at* P_{CUR}
  3. *Record* (P_{CUR}, M_{CUR})
  4. *Go to Step 4*
Step 4. *Calculate GPI*
  1. *Calculate* C_j
  $C_j = \sum_{i=1} w_{ijk} \cdot \frac{m_i,REF}{m_i,CUR}$
  2. *Calculate* C_k
  $C_k = \sum_{j=1} w_{jk} \cdot C_j$
  3. *Calculate GPI*
  $GPI = \sum_{k=1} w_k \cdot C_k$
  4. *Record* $(P_{CUR}, M_{CUR}, C_j, C_k, GPI)$
  5. *End*

where, $\sum w_{ijk} = 1$, $\sum w_{jk} = 1$, and $\sum w_k = 1$.

Diagnosis modeling

Once we obtain values of PCIs and GPI through an assessment model above, we can build causal relationships to find the cause of a phenomenon of the assessment result. These relationships make it possible to trace back the process parameters that significantly determine values of PCIs and GPI. For example, we can design a diagnosis model using a decision tree, which normally consists of a number of nodes and, in turn, each node represents an attribute with different instances that are used to classify test cases (Famili 1994). This decision tree-based diagnosis model can be visualized in the form of the reverse direction on the relationship tree in Fig. 4.

Prediction modeling

When a part is newly machined with the same process parameters that have been used, the assessment model can provide the corresponding GPI. However, the assessment model will not work when these process parameters have not yet been used. In this case, the prediction model can provide the predicted GPI for these process parameters.

When creating prediction models, we can choose an appropriate technique among available prediction modeling techniques such as k-means clustering, neural network, bayesian network, support vector machine and regression. Regression modeling is a commonly used technique because it can help create numerical regression models based on statistical analysis without domain specific knowledge. Equation (4) shows the pseudocode to create a prediction model by the use of a regression modeling technique. This regression model can predict the GPI from an input set of process parameters, but it requires the additional use of the assessment result data.

Step 1. *Initialization*
  1. *Set process parameter* $P(p_1, \ldots, p_i)$
  2. *Set measurement parameter* $M(m_1, m_2, \ldots, m_k)$
  3. *Set function of greeen productivity index (GPI)*
Step 2. *Experiment*
  1. *Determine factors for experiment*
  2. *Design the experiment*
  3. *Perform the experiment*
  4. *Record M set for each P*
  5. *Calculate GPI for each P*
Step 3. *Derivation of prediction model*
  1. *Set a method for prediction model*
  2. *Derive prediction model (the case of second order regression model)* (4)
  $GPI = f(p_1, \ldots, p_i) = \beta_0 + \sum_{i=1}^{n} \beta_i p_i + \sum_{i \le j}^{n} \beta_{ij} p_i p_j + \varepsilon$
  3. *Check accuracy of the model*
Step 4. *Estimation of GPI*
  1. *Input* $P_{EST}(p_{EST,1}, \ldots, p_{EST,i})$
  2. *Estimate* GPI_{EST}
  $GPI_{EST} = f(p_{EST,1}, \ldots, p_{EST,i})$
  3. *Output* (P_{EST}, GPI_{EST})
  4. *If the output is satisfactory, terminate process else, goto Step 4-1*

where, β coefficient, n number of independent variables, and ε error.

Optimization modeling

An optimization model is needed to find the process parameters that will maximize the GPI within constraints of the problem. Equation (5) presents the pseudocode to create an optimization model to identify an objective function, constraints and decision variables. This optimization model is based on the regression model described in the previous section. This optimization model is a single objective problem with multiple constraints, which is a common problem in optimization domain. We can also apply an appropriate optimization technique to solve this problem. Some examples of optimization techniques are (non-) linear programming, dynamic programming, genetic algorithm, tabu search and simulated annealing (Mukherjee and Ray 2006).

Step 1. *Initialization (Inheritance of Equation 4)*
1. *Set process parameter* $P(p_1, p_2, \ldots, p_i)$
2. *Set measurement parameter* $M(m_1, m_2, \ldots, m_j)$
3. *Set sub-PCI* (C_k) *and PCI* (C_m)
3. *Derive prediction model*
$$GPI = \beta_0 + \sum_{i=1}^{n} \beta_i p_i + \sum_{i \le j}^{n} \beta_{ij} p_i p_j + \varepsilon$$
Step 2. *Problem solving*
1. *Set problem*
objective function: Maximize(GPI)
$$\text{subject to } p_i^{(L)} \le p_i \le p_i^{(U)}, \quad m_j^{(L)} \le m_j \le m_j^{(U)}, \quad C_k^{(L)} \le C_k \le C_k^{(U)}, \quad C_m^{(L)} \le C_m \le C_m^{(U)} \tag{5}$$
2. *Solve problem using optimization technique*
3. *Return process parameter set* (P_{opt}) *and resultant value* (GPI_{opt})
Step 3. *Solution verification*
1. *Estimate GPI using prediction model*
2. *If result is acceptable, Record* (P_{opt}, GPI_{opt}) *else, goto Step* 2.

where, (L) lower limit, and (U) upper limit.

Experiment and prototype development

An experiment has been conducted with a turning machining process to show the validity of the GP planning model developed in "Implementation" section. This experiment takes the Design of Experiment (DOE) for efficient and controllable experiments (NIST 2014). A prototype system has been developed to show the applicability of the GP planning model. "Design of experiment" section describes the DOE, and "Data acquisition" section presents the data acquisition method and the measurement result. "Result of assessment", "Result of diagnosis", "Creation of the prediction model" and "Finding of optimal process parameters" sections, respectively, explain the results of assessment, diagnosis, prediction and optimization. "Prototype development" section introduces the prototype system and "Discussion" section discusses the result of the experiment and the prototype development.

Design of experiment

The DOE determines the purpose of the experiment, the objective functions, the independent variables, the dependent variables, constraints and a design method as described below:

- Purpose of the experiment: (1) the assessment of the GPIs by the sets of independent variables, (2) the creation of a diagnosis model and a prediction model by using the assessment result data, and (3) the finding of a set of process parameters to maximize the GPI within the ranges of independent variables
- Objective function: maximize the GPI
- Dependent variable: the GPI
- Independent variables (decision variables): feedrate, spindle speed and cutting depth
- Design method: the Box-Behnken design in a response surface methodology (Box and Behnken 1960). Table 2 shows the design factors and levels designed by the Box-Behnken method.

Data acquisition

Actual machining has been carried out, and the measurement parameters have been measured under the control of the DOE. Table 3 summarizes the machining condition used in this experiment. Table 4 presents the measurement values and the associated devices used to acquire these eight measurement parameters. Table 5 describes the measurement results of the measurement parameters for the fifteen trials where a center point (Trial 13) is set as the reference trial. Trial 14 and Trial 15 are used as calibration trials to adjust the center point.

Table 2 Factors and levels of the experiment

Factors	Level			Unit
	−	0	+	
Feedrate	0.23	0.25	0.27	mm/rev
Spindle speed	955	1273	1590	rpm
Cutting depth	2	2.5	3	mm

Table 3 Machining condition of the experiment

Property	Machining condition
Machine tool	2-axis turning machine tool
CNC	Fagor 8055T
Cutting tool & insert	Coated hard metal insert (Taegutec KNUX160405)
Workpiece	AL6061 cylindrical workpiece (radius: 25 mm, length: 75 mm)
Machining feature	General revolution (a linear shape swept by one complete revolution)
Machining operation	Contouring rough
Coolant	Water-soluble coolant (Castrol emulsion type)

Result of assessment

The assessment has been performed for the trials, based on the weighting factors indicated in Fig. 7 and the assessment model shown in Eq. (3). Table 6 presents the (sub-) PCIs and the GPI for the thirteen trials excluding the calibration Trials 14 and 15. Figure 8 shows the GPI portfolio that plots their greenability and productivity performances. Trials 6, 9 and 12 result in higher greenability and productivity values than those of the reference trial.

In this experiment, greenability correlates more to GPI than does productivity because the weighting factors imposed more importance to greenability. Productivity is biased more toward machining efficiency than toward production efficiency (see Fig. 7b). On the other hand, resource efficiency, energy efficiency and anti-toxicity have a balanced influence to the greenability. According to this result, this assessment model will recommend the process parameter set of Trial 9 (feedrate = 0.25, spindle speed = 955 and cutting depth = 2), which scores the highest GPI (1.071).

Result of diagnosis

A diagnosis model has been created to figure out influences of the process parameters on the positioning (Type I, II, III and IV) of each trial in the GPI portfolio of Fig. 8. We used a decision-tree learner from KINME with quality measure of Gini index (KNIME 2015). Figure 9 shows a decision tree where portions of the position types are distributed in terms of feedrate. In the first child nodes, the three trials positioned in the Type II area appear when feedrate is equal to or less than 0.24. On the other hand, all the trials in the Type IV are located in feedrate greater than 0.24. In the second child nodes, the two trials in Type IV are located in between feedrate of 0.24 and 0.26. One finding with statistical signifi-

Table 4 Measurement methods and devices in the experiment

Measurement parameter	Unit	Measurement value	Device
Machining time	s	The time consumed for the execution of a G-code part program	WinDNC v5.1
Power consumption	kW	The average electrical power consumed during machining. The power is obtained by dividing the sum of power values by the machining time	Yokogawa AP240E
Air pollutant	ppm	The maximum value of NO_2 emission during machining	Maxfor CM5000
Roughness	μm	The centerline average roughness (R_a) at temperature 16.2 °C and humidity 44 %	Mahr Perthometer M2
Tool use time	s	The approximate tool contact time represented by Eq. (6): $T = \frac{\sum L + \sum \Delta L}{F} \times 60 \quad (6)$ where, L(mm): feed length during contact, ΔL(mm): lift height, F(mm/min): feed per minute	Theoretical
Tool wear	–	The simplified relative comparison of Eq. (7) from (Choudhury and Kishore 2000) $W = (F_0 + mN_{cur}^a f_{cur}^b d_{cur}^c D_{cur}^d) W_0 \quad (7)$ where, W(μm): tool wear at the current, W_0(μm): tool wear at the reference, F_0(N): initial cutting force assuming 0, N: spindle speed, f: feedrate, d: cutting depth, D(mm): material diameter, m, a, b, c, d: coefficients assuming $m = 0.003$, $a = 1.623$, $b = 0.912$, $c = 1.162$, $d = 1.01$	Theoretical
Coolant loss	ml	The lost volume which subtracts recovered rate (63.4 ml/s) from injected rate (64 ml/s) and then multiplies the residual rate by the machining time	Manual
Chip mass	g	The value which multiplies the density of aluminum (2.7 g/mm^3) by removal volume	Manual

Table 5 Measurement results

Trial	Process parameter			Measurement parameter							
	Feedrate	Spindle speed	Cutting depth	Machining time	Power	NO_2	Roughness	Tool use time	Tool wear	Coolant loss	Chip mass
1	0.23	955	2.5	110.980	1.958	0.410	4.501	81.266	0.581	66.588	178.128
2	0.23	1590	2.5	74.170	2.429	0.490	4.484	48.811	1.330	44.502	178.128
3	0.27	955	2.5	97.940	1.866	0.420	5.791	69.226	0.673	58.764	178.128
4	0.27	1590	2.5	65.620	2.665	0.470	5.817	41.579	1.539	39.372	178.128
5	0.23	1273	2	97.790	2.123	0.390	4.501	68.855	0.715	58.674	178.128
6	0.23	1273	3	77.850	2.261	0.390	4.408	52.871	1.145	46.710	178.128
7	0.27	1273	2	86.300	2.181	0.380	5.826	58.654	0.828	51.780	178.128
8	0.27	1273	3	68.730	2.358	0.420	5.708	45.038	1.326	41.238	178.128
9	0.25	955	2	115.590	1.813	0.310	5.102	84.440	0.484	69.354	178.128
10	0.25	955	3	91.320	2.024	0.300	5.274	64.838	0.775	54.792	178.128
11	0.25	1590	2	77.110	2.461	0.420	4.880	50.717	1.107	46.266	178.128
12	0.25	1590	3	61.920	2.673	0.410	4.926	38.943	1.773	37.152	178.128
13	0.25	1273	2.5	82.410	2.255	0.380	4.713	56.088	1.000	49.446	178.128
14	0.25	1273	2.5	82.230	2.276	0.380	4.738	56.088	1.000	49.338	178.128
15	0.25	1273	2.5	82.490	2.244	0.380	4.658	56.088	1.000	49.494	178.128

Table 6 Assessment result of GPI and PCIs

Trial	Sub-PCI					PCI		GPI
	Machining efficiency	Production efficiency	Resource efficiency	Energy efficiency	Anti-Toxicity	Productivity	Greenability	
1	1.082	0.933	1.020	1.011	0.913	1.037	0.984	1.000
2	0.993	1.041	0.987	0.985	0.965	1.008	0.980	0.988
3	1.012	0.930	1.024	1.027	0.936	0.988	0.999	0.995
4	0.965	1.073	1.026	1.006	1.041	0.997	1.022	1.015
5	1.044	0.957	1.004	0.997	0.949	1.018	0.984	0.995
6	1.010	1.032	1.003	1.009	1.010	1.017	1.008	1.010
7	0.984	0.964	1.016	1.006	0.997	0.978	1.006	0.998
8	0.974	1.057	1.033	1.028	1.050	0.999	1.036	1.025
9	1.134	0.942	1.097	1.080	1.024	1.077	1.068	1.071
10	1.011	0.965	1.032	1.037	1.059	0.997	1.042	1.029
11	0.992	1.020	1.001	0.989	0.997	1.001	0.995	0.997
12	1.018	1.137	1.058	1.043	1.108	1.054	1.067	1.063
13	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000

cance is that feedrate can give an impact on productivity performance, as shown in the distributions of Type II and Type IV. This diagnosis mainly comes from the positive influence of low feedrate on roughness. The roughness is the measurement parameter highly-weighted to machining efficiency.

Creation of the prediction model

A prediction model has been created, based on the independent variables of Table 5 and their dependent variable of Table 6. Equation (8) expresses a full-quadratic regression model to predict the GPI ($R^2 = 89.3\%$, p value = 0.005) with the use of Minitab. Figure 10 shows the response surface plots of the regression model in terms of feedrate, spindle speed and cutting depth. As shown in Fig. 10a, b, the surfaces of the GPI have saddle-type patterns with regard to change of feedrate and spindle speed or feedrate and cutting depth. As presented in Fig. 10c, the surface has a concave upward pattern with regard to change of spindle speed and cutting depth.

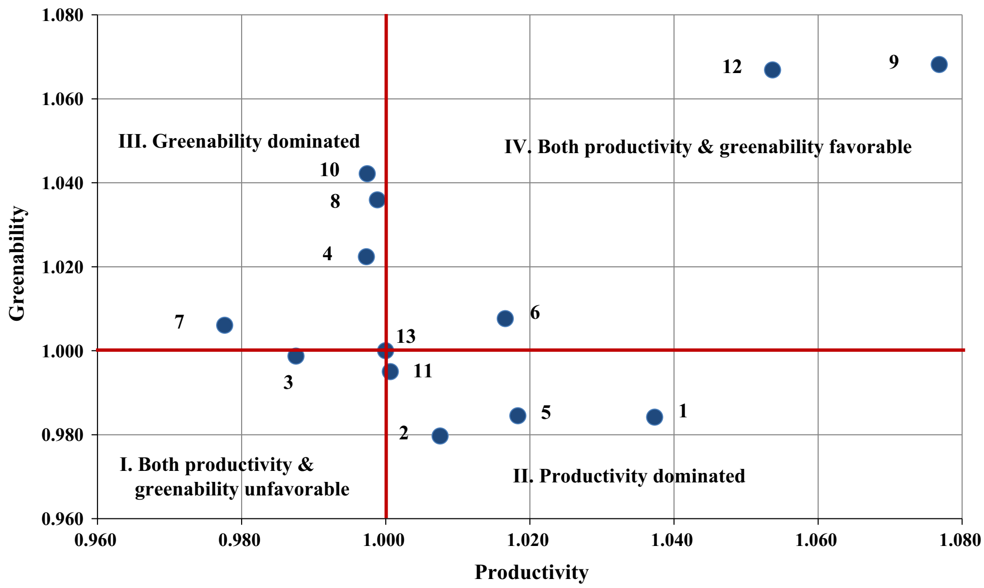


Fig. 8 A GPI portfolio of the assessment result

The deviation between a predicted GPI and a real-machined GPI with the same process parameters (feedrate = 0.2685, spindle speed = 1590 and cutting depth = 3) is measured to check the accuracy of the prediction model. The difference is measured as a 0.8 % deviation between the predicted GPI (1.068) and the real-machined GPI (1.060). This prediction model will be used to predict the GPI for the process parameter sets that are not used in the thirteen trials.

$$\begin{aligned} y &= 1.000 + 0.005x_1 - 0.005x_2 + 0.008x_3 - 0.017x_1^2 \\ &\quad + 0.016x_2^2 + 0.024x_3^2 + 0.008x_1x_2 + 0.003x_1x_3 \\ &\quad + 0.028x_2x_3 \\ x_1 &= \frac{X_1 - 0.25}{0.02},\ x_2 = \frac{X_2 - 1273}{317},\ x_3 = \frac{X_3 - 2.5}{0.5} \end{aligned} \tag{8}$$

where, y = GPI, X_1 = feedrate, X_2 = spindle speed, and X_3 = cutting depth.

Finding of optimal process parameters

An optimization model has been created, based on the constraints of the decision variables and Eq. (8) described in "Creation of the prediction model" section. Mesh segmentation of the decision variables in MATLAB is used. This optimization model finds an optimal set of process parameters (feedrate = 0.26, spindle speed = 1590 and cutting depth = 3) that indicates the highest GPI (1.075). Thus, this optimization model will recommend the use of this optimal process parameter set that can produce a higher GPI than that (GPI = 1.071) corresponding to the process parameter set (feedrate = 0.25, spindle speed = 955 and cutting depth = 2) recommended by the assessment model.

Prototype development

The prototype system consists of: (1) the on-line assessment module, which can collect machining data and immediately assess the GPI and PCIs in a shop floor, and (2) the post-line analytics module, which can provide the result of the assessment and predict the GPI by a certain input of process parameters. The post-line analytics module is implemented as a module of the TurnSTEP Code Generation System (CGS), which automatically recognizes machining features and their corresponding machining operations (Suh et al. 2006). The prototype system utilizes C++ as a programming language and Microsoft SQL server as a database.

Figure 11 visualizes the screen shots to explain main functions of the on-line assessment. Figure 11a shows the weighting factors that correspond to the values assigned by Fig. 7 and that have been already coded before on-line data collection. Figure 11b shows an example of the data collection to obtain values of the measurement parameters from the sensors described in Table 4. The list and graph of Fig. 11b indicate, respectively, the sensing data set of air pollutants (O_3, CO, SO_2, NO_2 and CO_2) and the time-series NO_2 profile during the *contouring_rough* machining operation stated in Table 3. Figure 11c shows the data set that aggregates values of the measurement parameters and those of the process parameters. Figure 11d depicts the result of on-line assessment by using the assessment model described in Eq. (3). A database records this data set that includes process parameters and their associating measurement parameters and assessment result.

Figure 12 illustrates the screen shots to explain main functions of the post-line analytics module. Figure 12a depicts the data set retrieved from the database. This post-line ana-

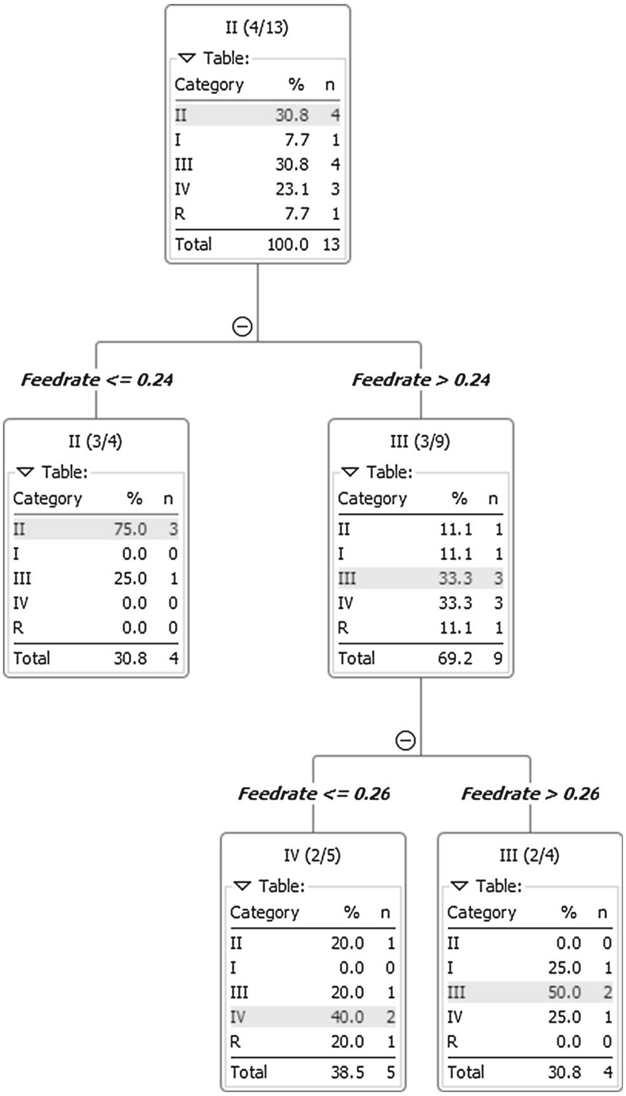


Fig. 9 A decision tree diagram of the diagnosis model

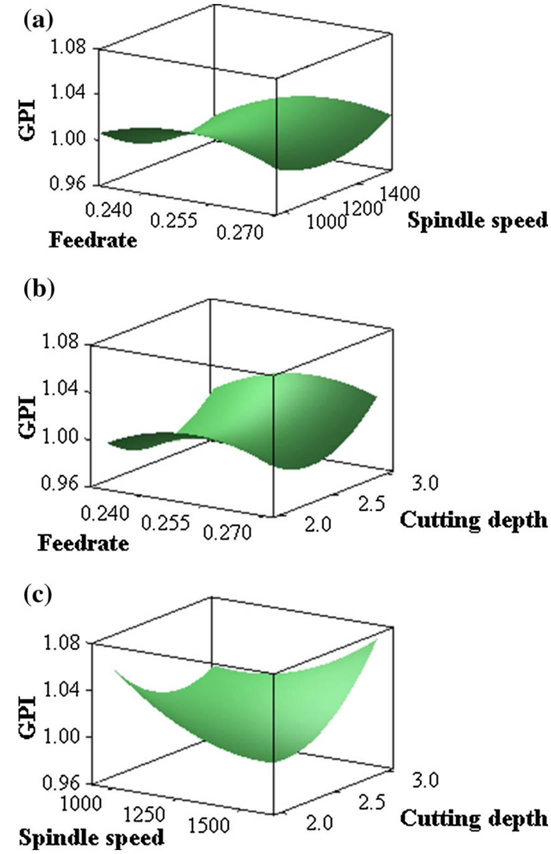


Fig. 10 Response surface plots of the regression model. **a** Feedrate, spindle speed versus GPI. **b** Cutting depth, feedrate versus GPI. **c** Spindle speed, cutting depth versus GPI

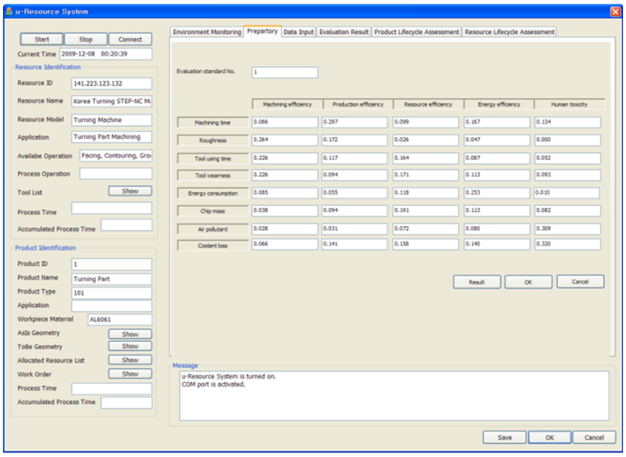
lytics module can recommend the process parameter set that gains the highest GPI for the machining operation. Figure 12b visualizes the prediction result from the input of a process parameter set.

Discussion

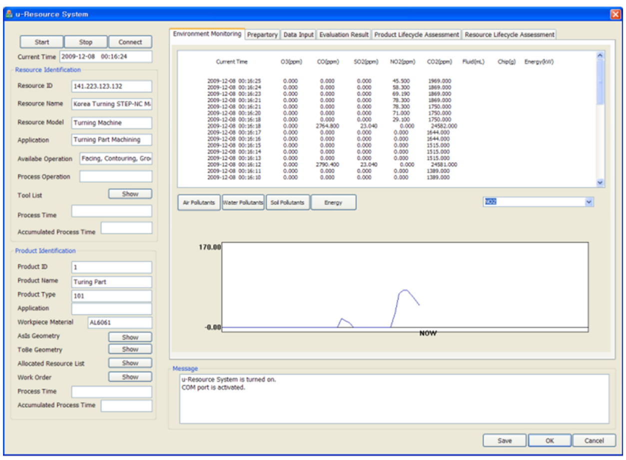
The experiment has shown the validity of the GP planning model in a machining system. Furthermore, the GP planning model has shown the applicability of the process-oriented LCA framework within a manufacturing system. This section addresses the distinction between the GP planning model and conventional process planning models as well as the necessity of the application of the framework.

- Validity of the GP planning model: the GP planning model determines the process parameters to maximize the GPI while conventional process planning models only determine these process parameters to maximize MRR within the capabilities of cutting tools and a machine tool. Figure 13 illustrates the logarithmic-scaled bar chart, where a shorter bar indicates a better performance. This figure compares the eight measurement parameters observed in Trial 9 (the trial involving the maximum GPI) with those in Trial 12 (the trial involving the maximum MRR). Trial 9 gains improved power consumption, air pollutant and tool wear than those of Trial 12. As these measurement parameters correlate more to greenability than to productivity, the GP planning model can determine greenability-favorable process parameters better than conventional process planning models. Thus, greenability can be now considered as a major performance indicator to determine the process parameters for a machining system.
- Applicability of the process-oriented LCA framework: the GP planning model shows that the application of the framework enables manufacturers to derive process parameters that improve the GP performance through the gradual use of assessment, prediction and opti-

(a)



(b)



(c)

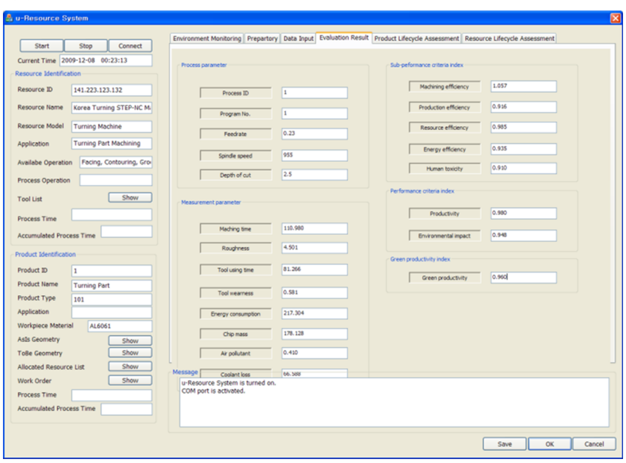
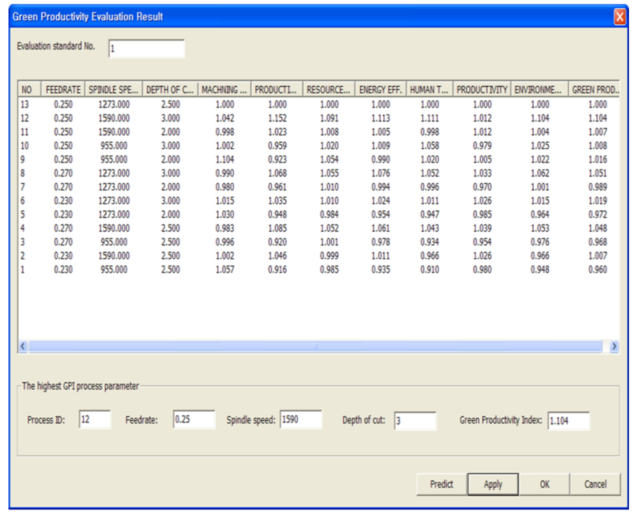


Fig. 11 Screen shots of the on-line assessment module. **a** Set up of weighting factors. **b** On-line measurement of air pollutants. **c** Result of on-line assessment

mization models without major decrease in productivity. It also shows that the application of this framework enables manufacturers to perform timely decision-making through the acquisition of the machining data col-

(a)



(b)

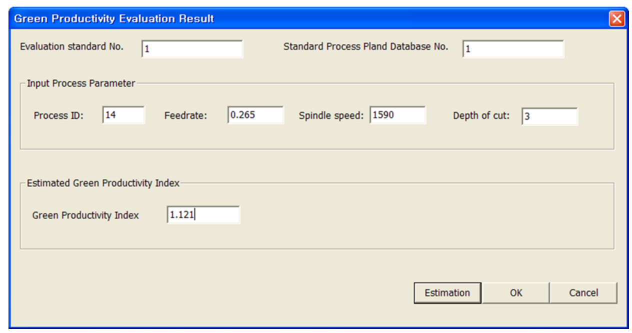


Fig. 12 Screen shots of the post-line analytics module. **a** A list of on-line assessment result. **b** Result of prediction by the input of a process parameter set

lected from measurement devices and the process instantiation of the data. It may be possible to implement the GP planning model without this framework, but this may require much trial-and-error and intensive knowledge because this cannot assure the holistic and robust implementation necessary to improve the GP performance in complex manufacturing processes. Meanwhile, the application of this framework can help to efficiently achieve the improvement of the GP performance in manufacturing processes through the systematic method specified here.

Conclusion

This paper presented the development of the process-oriented LCA framework to help implement the eco-manufacturing environment in manufacturing processes. This framework is a systematic and structural method to support process-oriented decision-making on the basis of the manufacturing

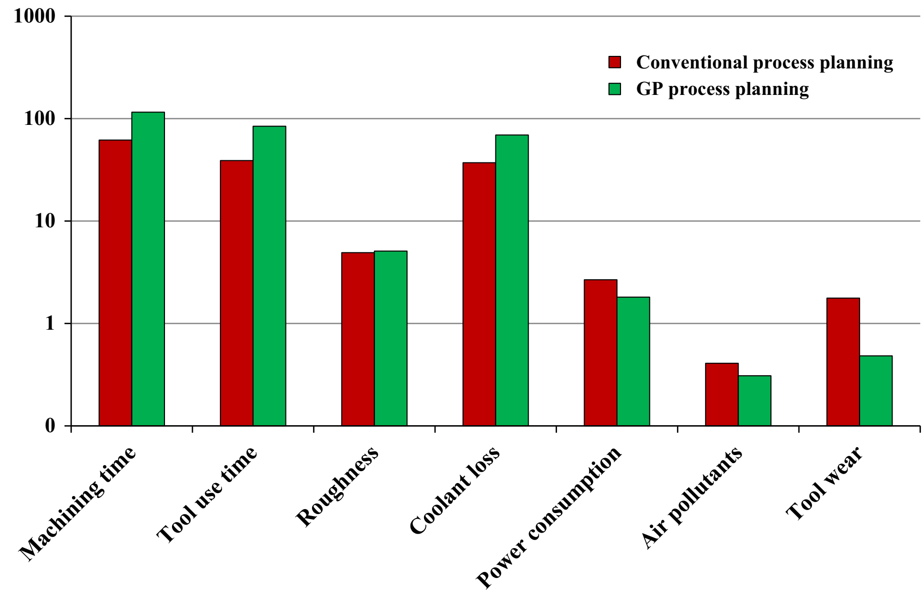


Fig. 13 A comparison of the maximum MRR trial and the maximum GPI trial

data collected from manufacturing systems. It can assess, diagnose, predict and optimize the GP performance in manufacturing systems. This paper also presented the applicability of this framework through the GP planning model and its relevant experiment. The experiment showed the maximization of positive performances and simultaneously the minimization of negative performances for the balanced improvement of greenability and productivity.

The proposed framework will gain more practicability for real industries when it can foster the environment for greenability-measurable data acquisition, real-time prediction and optimization, and model-driven knowledge base implementation. First, the data acquisition is the critical step for improving GP performance; however, in reality, the lack of measuring devices and methods frequently makes the data acquisition unavailable during production and thus the GP improvement interrupted. This is why more options for the data acquisition should be considered, as mentioned in "Data acquisition" section. An alternative for increasing the data availability is the integration of the proposed framework with feasible data acquisition frameworks such as the deliverables of Zein et al. (2011) and Peng and Xu (2014). Second, the proposed framework has been structured to make timely predictive and optimal decisions rather than real-time control because this framework has more focused on making planning and control decisions for manufacturing processes. The adoption of real-time prediction and optimization for in-process control can increase the practicability of this framework in the case that manufacturing processes requires higher precision and cost (Jiang et al. 2014). Third, assessment, prediction and optimization models will vary in terms of the combination of manufacturing processes, machines, materials, tools, products and objective functions. The performance criteria and their associating weighting factors (e.g., Fig. 7) can also vary depending on experts' determination. In this sense, a shop floor will require the application of hundreds or thousands of instances of these models for its manufacturing operations. Therefore, an intelligently organized knowledge base needs to be implemented to design and operate efficiently these multiple instances of the models. This knowledge base will enable reusable and extensible applications of the models for increasing the practicability of this process-oriented LCA framework.

Some limitations of this paper are that: (1) the process-oriented LCA framework has been implemented only to a machining process, and (2) it still contains a qualitative method based on subjective weighting. The future works include to: validate the applicability of this framework to various and complex manufacturing processes, enhance the robustness of this framework through the application of quantitative methods, and improve the practicability of the process-oriented LCA framework.

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