A Decision Guidance Framework for Sustainability Performance Analysis of Manufacturing Processes

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ABSTRACT

Life-Cycle Assessment (LCA) methods are widely used to assess the sustainability of manufacturing processes. Although it has several advantages such as systematic estimation and efficiency, LCA has limited functionality. For example, it does not support decision optimization and parameter calibration. Additionally, it does not provide a unified modeling environment in which to perform a sustainability analysis. In this paper, we present a decision guidance framework that addresses these deficiencies. That framework consists of six phases: goal and scope definition, data collection, model generation for process and analytics, sustainability performance analysis, interpretation, and decision support and guidance. To demonstrate the use of the framework, we include a case study of a turning process. We also discuss and evaluate the feasibility of the framework in terms of functionality, usability, flexibility, reusability, and interoperability.

Keywords

Sustainable manufacturing, sustainability analysis, decision support and guidance, manufacturing processes, and machining process.

1. INTRODUCTION

Manufacturing industries are under intense social and competitive pressures to reduce the environmental impact of their products and processes. Sustainable Manufacturing (SM) addresses these pressures. Its goal is to achieve a global competitive edge, while taking into account environmental, societal, and economic factors [1]. Research and development (R&D) efforts related to SM aim to increase the economic and societal benefits throughout the product life-cycle. These efforts cut across different organizational boundaries and technological issues [2, 3]. To date, however, most of these R&D efforts have focused on product sustainability; far fewer have focused on process sustainability [4]. A commonly used method in these product efforts is Life-Cycle Assessment (LCA).

LCA provides functions and procedures to assess accurately the environmental impacts of products. Currently, however, it does not support decision optimization and parameter calibration, which could reduce those impacts. LCA also does not provide a unified modeling environment across the life cycle. These additional capabilities have been recognized as key enablers for sustainability improvements [5, 6]. Linking these capabilities to LCA will not be easy [7, 8]. Without them, however, manufacturers, particularly small and medium enterprises (SME), will continue to struggle to make informed decisions that improve sustainability.

Several international efforts such as the CO2PE! Initiative [9] and Ecoinvent [10] have recognized the need for these added capabilities. The CO2PE! Initiative is a coordinated, international effort to collect, document, and assess the environmental impacts of conventional and emerging manufacturing processes. Ecoinvent has developed a database, containing lifecycle inventory (LCI) data. It has also specified an LCI data exchange format for use with LCA software. Although these efforts extend the scope of LCA to include manufacturing processes, they still focus only on assessment. Therefore, a comprehensive and systematic framework that includes the aforementioned decision-making capabilities still does not exist.

This paper proposes such a framework, which we call a decision guidance framework. That framework includes procedures and guidelines for different types of sustainability analyses and a unified modeling environment. It consists of six phases: goal and scope definition, data collection, model generation, sustainability performance analysis, interpretation, and decision support and guidance. A case study of a turning process is performed to demonstrate the use of the framework. Energy consumption and nitrogen dioxide (NO_2) are sustainability indicators in this case study. Optimal manufacturing parameters are derived through what-if analysis and decision optimization.

The paper is organized as follows. Section 2 explains the related work and the requirements for the decision guidance framework. Section 3 presents our framework. Section 4 includes a case study of a turning process. This case study shows the feasibility and effectiveness of the framework and demonstrates how the framework can be applied to a real-world problem. Section 5 evaluates the framework qualitatively in terms of functionality, usability, flexibility/reusability, and interoperability. Section 6 provides a conclusion and future work.

2. BACKGROUND

2.1 Related work

The idea of LCA was started by the international scientific society of environmental chemists, Society of Environmental Toxicology and Chemistry (SETAC). SETAC launched the Life-Cycle Initiative to provide life-cycle concepts, data, tools, and services. The International Standards Organization (ISO) subsequently initiated a global standardization process for LCA. Four standards were developed and issued in the ISO 14000 series of standards for Environmental Management, (ISO 14040-14043 [11-14]). The LCA framework in ISO 14040 consists of four modules: goal and scope definition, inventory analysis, impact assessment, and results interpretation. For more details, overview and survey papers can be found in [15].

Although LCA is a powerful methodology to assess the environmental impact, it has, as noted above, several limitations when it is used directly for decision support or process improvement. First, it lacks the mathematical foundations needed to support optimization. Second, it lacks the adaptability needed to deal with dynamic shop floor conditions. Third, it lacks the flexibility needed to incorporate different kinds of analysis tools. These limitations are well known, and several researchers have attempted to address them. Kellens et al. proposed [16] and demonstrated [17] a methodology for systematic analysis and improvement of sustainability. Jawahir et al. [18] proposed an innovation-based 6R - reduce, reuse, recycle, recover, redesign, and remanufacture - methodology to achieve optimized technological improvements and process planning. Pusavec and Kopac et al. [19, 20] presented methods and performed case studies to improve sustainability of machining processes. They concluded that such improvements can reduce total life-cycle costs.

2.2 Requirements analysis for the framework

We have divided high-level requirements into four categories ‘functionality’, ‘usability’, ‘flexibility\reusability’, and ‘interoperability’. The following paragraphs briefly explain each of these categories.

‘Functionality’ includes functions that 1) perform model formulation and composition for various sustainability performance analyses, 2) yield an application-independent, unified modeling environment, 3) provide reliable results and recommendations for improvements, and, 4) provide parameter calibration, modeling verification and validation, uncertainty quantification, sensitivity analysis, and integrity constraints.

‘Usability’ includes 1) the ‘tradeoff between simplicity and sufficient expressiveness’ for modeling and representation, 2) a ‘graphical representation’ that allows stakeholders to perform modeling tasks intuitively using a graphical user interface, 3) ‘readability’ that allows the models to be understandable, interpretable for sharable among humans, and 4) ‘well-defined semantics’ that reduce misunderstandings between different stakeholders.

‘Flexibility/reusability’ helps handle the broadness and complexity of the problems and enables stakeholders to reuse, modify, or exchange processes-related sustainability indicators and metrics. ‘Hierarchical representation’ and ‘extensibility’ are required to increase flexibility; ‘modularity’, ‘searchability’, ‘modifiability’, ‘storability’, and ‘configurability’ are necessary for reusability.

‘Interoperability’ is required for various methodologies, standards, file formats, structures, and systems to work together. ‘Methodology independency’, ‘compatibility with standards’, ‘transformability’, ‘platform-independency’, and ‘machine readability’ are the five requirements for interoperability.

Based on an analysis of these requirements, we concluded that none of the currently used LCA approaches can satisfy all of them. Therefore, a new comprehensive and systematic framework is needed.

3. THE PROPOSED DECISION GUIDANCE FRAMEWORK

Figure 1 shows the proposed framework that consists of six phases: a goal and scope definition, data collection, model generation, sustainability performance analysis, interpretation, and decision support and guidance. Similar to the LCA methodology [11], this framework supports incremental and iterative analysis; and, each phase can be revisited or reexamined several times. A brief description of each phase is given below and detailed explanations are provided in the following subsections.

Goal and scope definition: defines the goal and scope of the target manufacturing processes, the types of performance analyses to be completed, and the characterization factors to be used in those analyses.

Data collection: identifies and collects the sustainability data required to perform those analyses.

Model generation: generates computer-interpretable information models to represent the data and performance models need to analyze that data.

Sustainability performance analysis: uses the information and performance models to complete the performance analyses, including uncertainties, defined by the goal and scope.

Interpretation: completes an uncertainty quantification to interpret the outputs from the performance analyses and provide those outputs to other stages.

Decision support and guidance: uses interpreted outputs to make final recommendations based consensus of stakeholders (e.g., analysts, decision makers, and engineers).

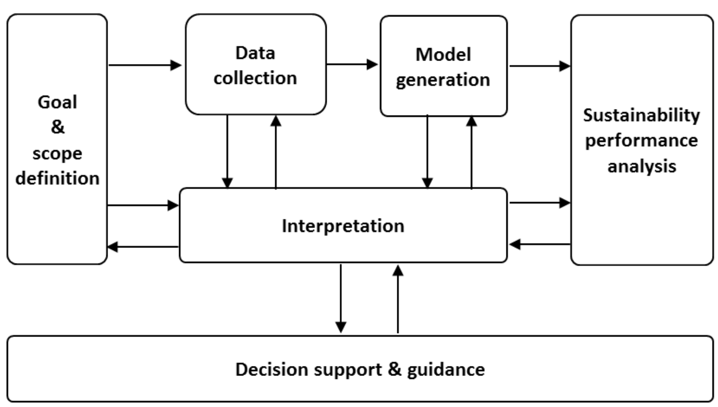

Figure 1. The proposed decision guidance framework.

3.1 Goal and scope definition phase

Figure 2 shows the procedures in the goal and scope definition phase as well as its interrelationship with other phases. This phase consists of five procedures: definition of the study goal, definition of the scope and system boundaries, determination of the sustainability indicators and metrics of interest, determination of the constraints and variables, and, generation of an abstract performance mathematical model. The information defined, determined, and generated in this phase will be inputs for the ensuing phases. The details of each procedure will be explained as follow.

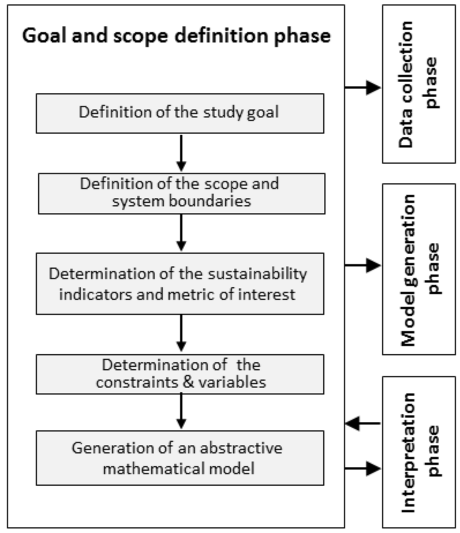

Figure 2. Procedures in goal and scope definition phase and Interrelationship with other phases.

Definition of the study goal: a study goal needs to be clearly understood to avoid incorrect results and wrong decisions. That goal specifies the reason for the study. Examples of goals include 1) assess the environmental impacts of a painting process, do a cost/benefit analysis to compare a conventional vs additive manufacturing.

Definition of the scope and system boundaries: the scope and system boundaries determine what processes will be included in the sustainability assessment. Those processes can be characterized using Input-Process-Output (IPO) method [21] or the methodology by the CO2PE! [16]. In this paper, we have used the methodology by the CO2PE! to characterize all processes and sub-processes, as shown in Figure 3. Figure 3 shows that manufacturing processes can be analyzed and decomposed along two separate axes: physical- and manufacturing- cycle-based decomposition. The "three dots" (¨) indicate that decomposition can result in several sub-processes between the two main processes. The physical-based decomposition is based on a spatial hierarchy. For example, Jiang et al. [21] analyzed and assessed a process plan that consists of turning, milling, drilling, and grinding. The turning process can be considered as sub-process I-I, while the grinding can be considered as sub-process IV-I. In addition, manufacturing processes can be decomposed using a temporal decomposition [22]. A machining process, for example, can be decomposed into four activities: setup, idle, active, and teardown.

Determination of the sustainability indicators and metrics of interest: determination of indicators and metrics is closely related to a data collection plan. Sustainability indicators and metrics for machining processes have been reported in [16, 18, 22]. Examples provide by Lu et al. [23] include 1) economic factors such as labor cost, energy cost, and material cost; 2) environmental factors such as wastes, NO_2 emissions, and carbon footprint; and 3) societal factors such as operational safety, human health, and ergonomics.

Determination of the constraints and variables: to generate an abstract performance model input variables, output variables, and constraints must be identified. Identification will depend on the nature of that model [24].

Generation of abstract mathematical models: an abstract mathematical model is generated based on the outputs from the previous procedures. This model is chosen to conform to the stated goals, boundaries, and required information. The abstract mathematical model is used for different kinds of sustainability analyses.

3.2 Data collection phase

The data collection phase provides the necessary data to run for performance models. As shown in Figure 4, the data collection phase includes four procedures: 1) data collection plan, 2) model existence check, 3) data collecting, and 4) determination of characterization factors. Each procedure is explained below.

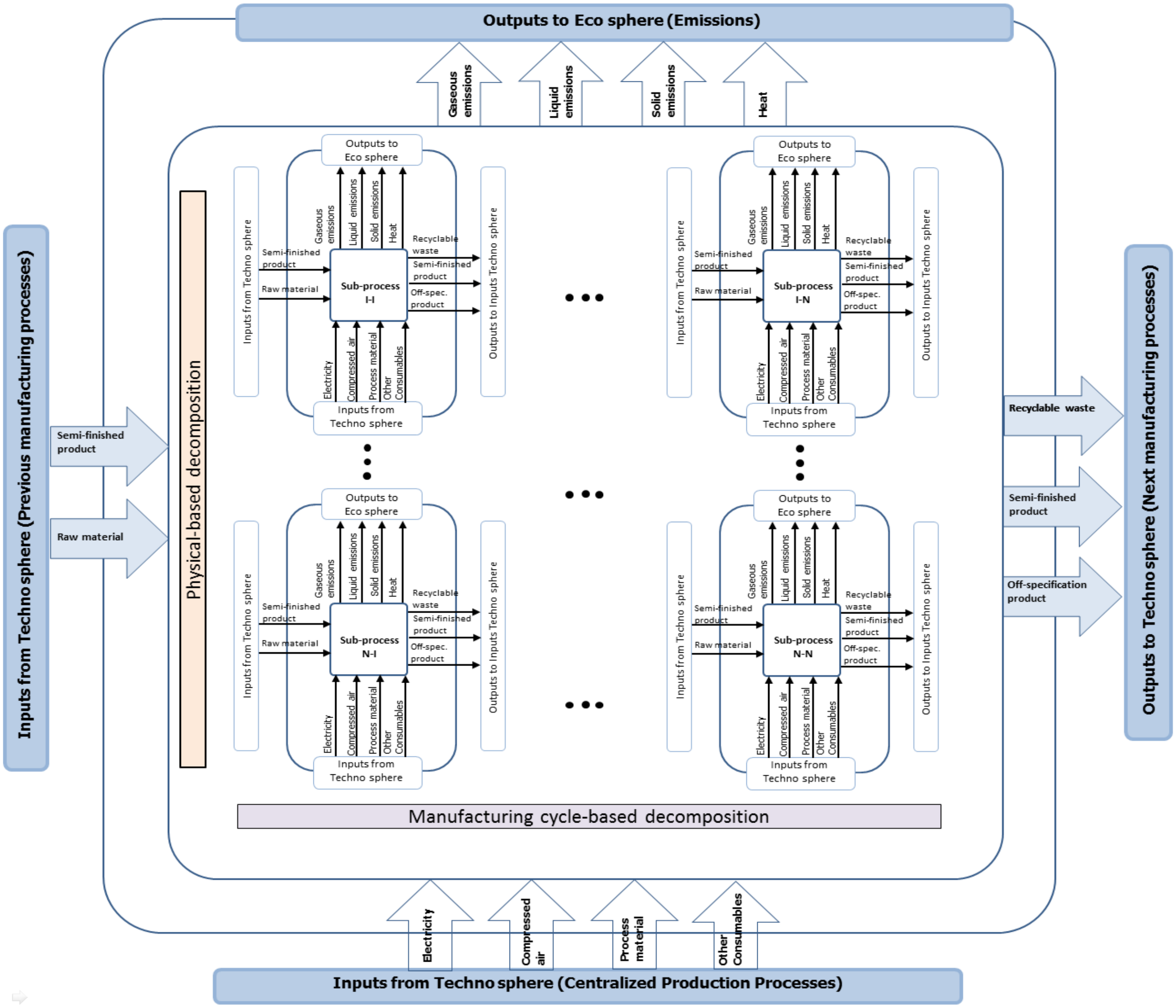

Figure 3. System boundaries and the information flow of manufacturing processes based on the CO2PE!

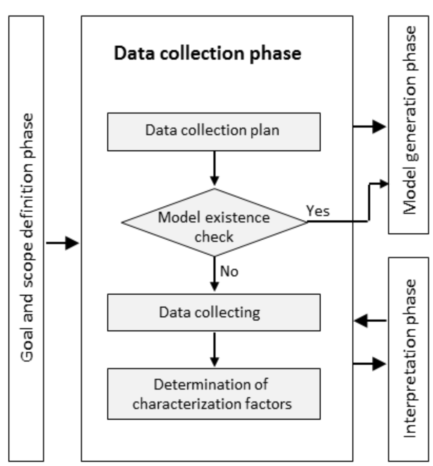

Figure 4. Procedures in data collection phase and Interrelationship with other phases.

Data collection plan: to minimize cost and effort, data collection must be well-planned. That data, which will come from multiple sources, can be categorized into quantitative and qualitative data [23]. The data collection plan not only determines the sources for collecting data, but also ensures that the quality and the accuracy meet the expectations of users.

Model existence check: a model checking determines whether the required data or models are available already. If not, the required data must be collected and a new model generated.

Data collecting: the collected data provides inputs to the performance model. Quantitative data can be collected from 1) manufacturers' repository systems, 2) measurements using software or sensors, 3) simulation systems, 4) direct empirical experiments, and 5) from analytical calculations. Qualitative data can be obtained by using the soft computing techniques - such as fuzzy-logic, neural networks, and genetic algorithms - that convert subjective knowledge/opinion into a mathematical formulation [26].

Determination of characterization factors: characterization factors (e.g., scaling, normalization, and weighting) and aggregation methods should be determined. The collected data needs to be normalized and quantified in a scientific and objective manner, since each indicator is commonly measured in different unit systems (e.g., kilo-Joule for energy and liter for coolant consumption) and some input data is qualitative and dimensionless (e.g., human safety and health). Weighting factors of each indicator at specific levels can affect the analysis results significantly. They should be carefully defined. The normalization and weighting factors are mainly obtained based on the consultation (e.g., survey from experts and statistical methods) [27, 28]. For example, Jawahir et al. [8, 18, 23] identified the manufacturing cost, personnel health, operational safety, waste management, energy consumption, and environmental impact as the six significant contributors to the SM processes and proposed an integrated approach for characterization factors.

3.3 Model generation phase

The model generation phase takes the information collected from the selected process and the model selected from available performance models and integrates them to form a model that is in some generic, neutral format. Figure 5 shows the procedures in model generation phase and interrelationship with other phases. This phase consists of three procedures: manufacturing process modeling, analytics modeling, and an integrated SM process model. The output of this phase is a generic model that incorporates process and analytics knowledge for multiple sustainability analyses.

Manufacturing Process modeling: creates a model that describes a specific manufacturing process, its inputs, and its outputs as shown in Figure 3. Inputs from technosphere I include information flows that describes the workpiece and raw materials to be processed. Inputs from technosphere II include information flows associated with the consumables used by the activities - setup, idle, and teardown - associated with the manufacturing process. Examples of consumables include electricity, compressed air, and coolants. The model of the physical manufacturing process can be represented in a number of ways including mathematical equations or dynamic simulations. Outputs to ecosphere are modeled as information flows that represent various environmental impacts from the physical manufacturing processes. Examples of these outputs include recyclable waste, CO_2, and, NO_2 to name a few. The outputs from process modeling include all of the aforementioned models.

Analytics modeling: chooses from available predictive models for sustainability. Model types include analytical, numerical, empirical, and Artificial Intelligence (AI) [18]. Since SM contains various complexities and uncertainties, analytical models can provide an effective and efficient method for analytics [18]. A numerical analysis is widely used to analyze sustainability data [18], which includes a variety of specific techniques such as simple calculation, interpolation, regression, and finite element methods. Empirical methods can quantify subjective experiences and opinions into digitized values. The qualitative and quantitative sustainability data can be also modeled based on AI-based model, such as fuzzy-logic, neural network, and genetic algorithm [26]. In addition, we have included a sustainability impact model, which includes mathematical formula for calculating a sustainability single score, should also be generated. The output from analytical modeling includes all of the models that will be used to calculate the sustainability metrics for this particular manufacturing process.

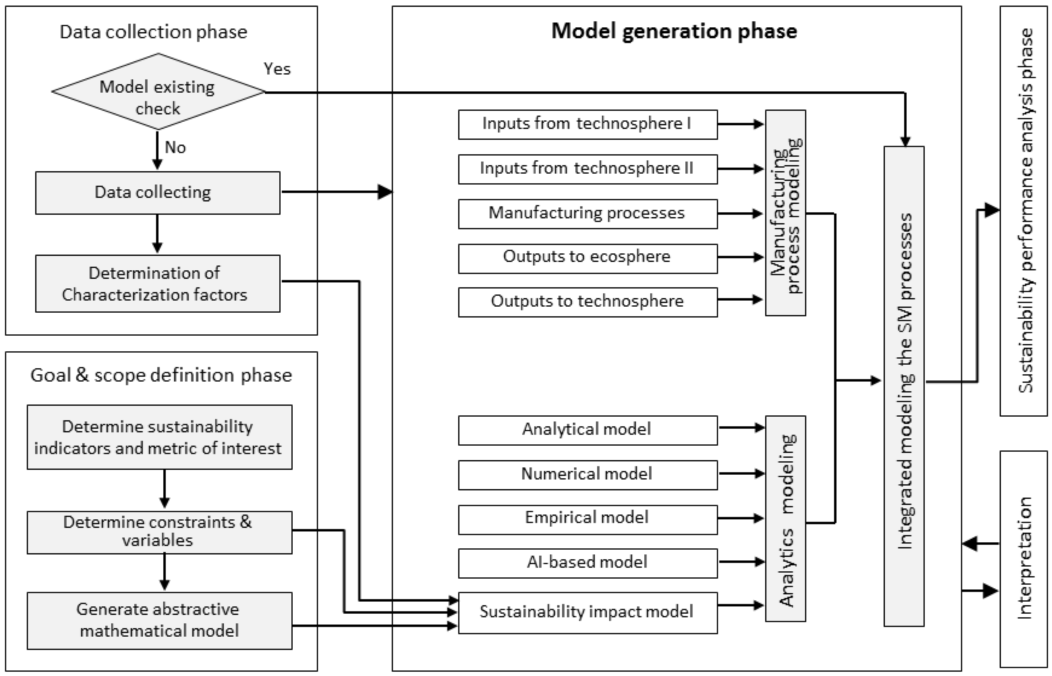

Figure 5. Procedures in model generation phase and Interrelationship with other phases.

Integrated Modeling the SM processes: The selected analytics models require certain inputs. These inputs come from the outputs of the manufacturing process modeling. As noted above, these outputs come in two forms: information flow models and physical process models. Therefore, the formats of these outputs must match the input requirements of the analytics models. If they don't, then numerous translations will be necessary. To facilitate these translations, we will use a recently develop modeling language called Sustainable Process Analytics Formalism (SPAF) [29]. We chose SPAF over other modeling languages such as BPMN [30], SysML [31], and PSL [32], because SPAF was designed specifically for SM applications. More importantly, SPAF provides a mechanism to represent information models, process models, and analytics models, and a variety of sustainability metrics in a common language. The resulting SPAF integrated model is the principal output from this function.

3.4 Sustainability performance analysis phase

This SPAF model proivdes the sole input into the sustainability performance analysis phase. As shown in Figure 6, this phase has three procedures i.e., translation, analysis tasks, and results extraction. Several analysis tasks such as query analysis, what-if analysis, and optimization analysis can be performed. The derived results need to be provided to the interpretation phase for accuracy and reliability check.

Translation: the SPAF neutral models must be translated into application-specific models in certain formats. These formats are required to run the various analysis tasks.

Analysis tasks: the applications-specific models can then be executed using different commercial analysis tools and solvers for query analysis, what-if analysis, and optimization analysis. Query analysis is denoted as "an analysis process of finding the value of interest in manufacturing processes from the searching in database and delivering the queries dataset to the users". What-if analysis is defined as "an analysis process of computing and comparing the different outputs of the model by changing the inputs such as process parametersand conditions to evaluate alternatives and decide prefered settings.". Simulation and LCA are under this caterogy. Optimization analysis is explained as “an analysis process of searching optimal values for various process parameters that satisfy certain conditions and constraints with an objective function”.

Results extraction: after performing the sustainability analysis tasks, several types of results can be extracted. Each result can be used to aid in the final decisions.

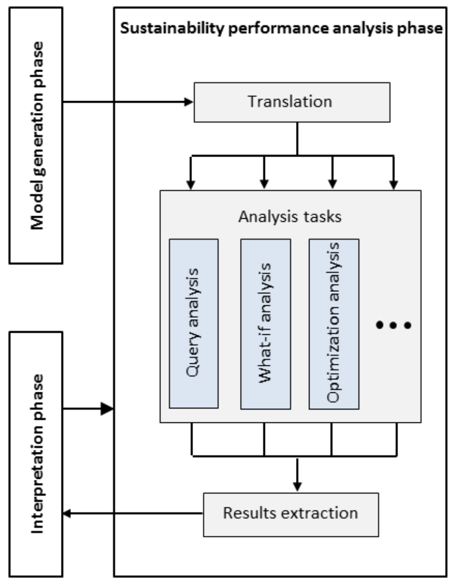

Figure 6. Procedures in sustainability performance analysis phase and Interrelationship with other phases.

3.5 Interpretation phase

The extracted results contain uncertainties that can arise from a number of sources. These uncertainties are important because they can lead to discrepancies between the model results and reality. This, in turn, can lead to to incorrect decisions. It is imperative, therefore, to identify and characterize these sources and we need quantify the associated uncertainties. As shown in Figure 7, an interpretation phase consists of identification of significant issues, identification of types and sources of uncertainties, and investigation with interpreting modules. Such modules could include validation and verification (V&V), uncertainty quantification (UQ), sensitivity analsysis (SA), parameter calibration (PC), and integrity constraints (IC).

Identification of significant issues: due to the amount of data collected, it is only feasible within reasonable time and resources to investigate the data elements that contribute significantly to the outcome of the results. Identifing the signficant issues to the results is the first step for interpretation.

Identification of types and sources of uncertainties: uncertainties can be categorized as either aleatory, epistemic, or a mixture of two [33]. Aleatory uncertainties come from the inherent variation or randomness in processes. This means that aleatory uncertainties are very difficult to reduce. On the other hand, epistemic uncertainty comes from uncertainties in the model or the data. In addition, there are four main sources of uncertainty: model inputs, model assumptions, model form, and numerical approximations [33]. As a result, epistemic uncertainties can be reduced with a more-accurate model, more detailed knowledge, or better data. If there a percieved problem, these are the first places to look for a solution.

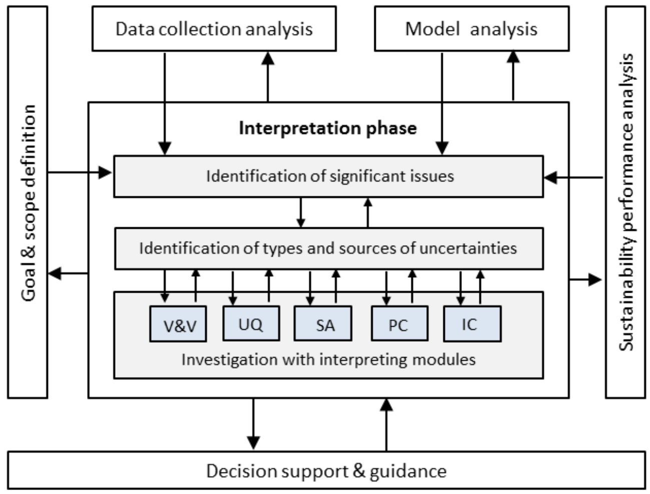

Figure 7. Example of interrelationship between Interpretation phase and other phases.

Investigation with interpreting modules: this procedure provides the understanding of the uncertainties and assumptions. In a V&V module, verification addresses the estimation of numerical errors (e.g., discretization error, iterative error, and round-off error), while the assumption in the model is usually addressed through model validation [33]. The UQ module is denoted as the science of quantitative characterization and reduction of uncertainties. The objective of SA is to evalute and identify the significant inputs. The PC module is to tune the parameters with respect to the dynamic shop floor conditions. The IC module is used to maintain accuracy and consistency of data, model, and metric unit system used throughout all phases.

3.6 Decision support and guidance phase

In the decision support and guidance phase, stakeholders reach a final recommendation (decision) based on the results from interpretation phase. The process used to make this recommendation has, as shown in Figure 8, three procedures: reporting the results to stakeholders, critical review, and final recommendation.

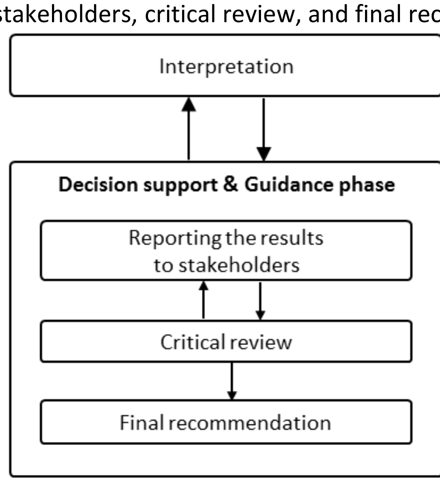

Figure 8. Procedures in decision support and guidance phase.

Reporting the results to stakeholders: once the study is completed, the results must be gathered into a comprehensive report for all stakeholders. The report provides the results, data, methods, assumptions, and limitations in detail to enable the stakeholders to clearly understand the context of the study.

Critical review: Stakeholders will form are panel review the results before making a final recommendation.

Final recommendation: based on the discussion, consensus, and critical review by the stakeholders, the final actionable recommendations can be provided to decision makers.

4. CASE STUDY

To demonstrate how to use the six steps in our approach, we present a case study based on a turning process. Section 4.1 defines the goal and scope. Section 4.2 builds the data collection plan and collects the data referred from [34]. In Section 4.3, an integrated model from the process and analytics models is generated using SPAF. It provides the inputs for assessment analysis (SimaPro) [35], and it is translated into Optimization Programming Language (OPL) format [36] for optimization analysis. The assessment results as well as the optimal manufacturing parameters are derived in Section 4.4. Section 4.5 interprets the derived results through validation and parameter calibration. Finally, the decision recommendations are provided in Section 4.6.

4.1 Goal and scope definition phase

Definition of the goal of the turning process: the goal of this case study is to determine optimal process parameters, spindle speed, feedrate, and cutting depth, of a turning process, which imposes the minimal environmental burdens. This turning process inputs a cylindrical workpiece sized by 50 mm length and 50 mm diameter as shown in Figure 9 (a), and outputs a machined part as shown in Figure 9 (b). Only roughing operation is considered for the study, and Geometrical Dimension and Tolerance (GD&T) is ignored.

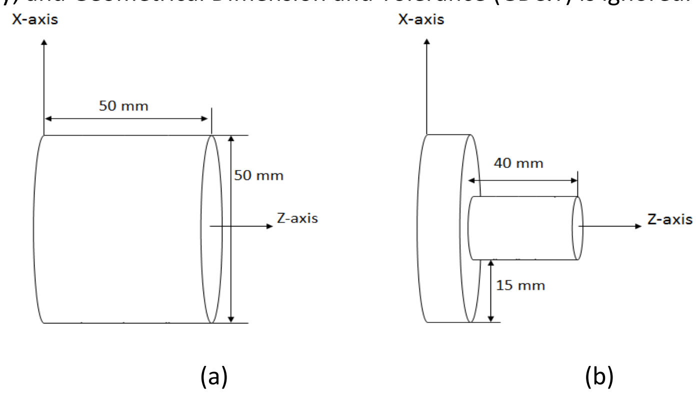

Figure 9. Shape and size of geometry workpiece (a) and its output product (b).

Definition of the scope and system boundary: as presented in Section 3.1, the turning process is decomposed into multiple sub-processes by using manufacturing cycle-based decomposition method. The turning process can be sub-divided into setup, idle, active, and teardown. Each sub-process has its own inputs from technosphere, and outputs to ecosphere and technosphere.

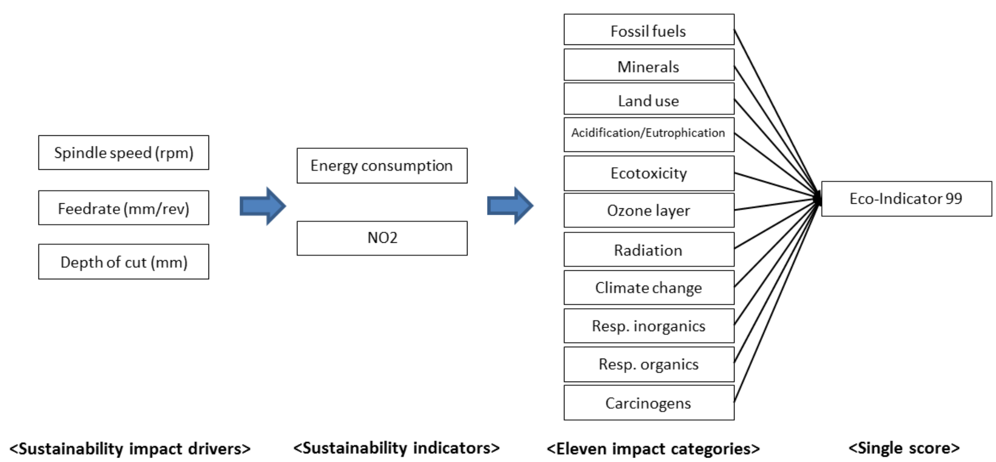

Figure 10. A flow of single score estimation of Eco-indicator 99 from the sustainability impact drivers.

Determination of the sustainability indicators and metrics of interest: We used the impact assessment method described in Eco-indicator 99 [37] to estimate two main sustainability indicators: energy consumption and nitrogen dioxide (NO_2) emission. Figure 10 shows the logical flow of a single scoring of Eco-indicator 99 starting from the sustainability impact drivers. The impact drivers indicate the process parameters (i.e., spindle speed, feedrate, and cutting depth), because the drivers affect the indicators. The indicators are classified into the eleven impact categories. Finally, a single score can be obtained from aggregation of values of the eleven categories.

Determination of the constraints and variables: the decision variables are cutting depth, spindle speed, and feedrate, since they significantly impact machining and environmental performances. The constraints are set to (2, 3) mm for cutting depth, (955, 1590) rpm for spindle speed, and (0.23, 0.27) mm/rev for feedrate, respectively. The ranges are assigned from reviewing the allowances stated in the cutting tool catalogue.

Generation of the abstractive mathematical model: before planning a data collection, abstract mathematical models are prepared. The abstract models for energy consumption, NO_2 emission, and a sustainability single score are shown as follows.

Energy consumption: as defined in Section 4.1, the total energy consumption (E_{total}) consists of energy consumption from the four sub-processes as below:

$$E_{total} = E_{setup} + E_{idle} + E_{active} + E_{teardown}. \qquad \text{(Eq. 1)}$$

Each energy consumption for the setup (E_{setup}) and teardown ($E_{teardown}$) modes is a constant, whereas those of idle (E_{idle}) and active (E_{active}) are dependent on machining performance. The energy consumption for setup and teardown will be measured in data collection phase in Section 4.2. The energy consumption for active mode is calculated as below:

$$E_{active} = P_{active} \times t_{active}. \qquad \text{(Eq. 2)}$$

The power consumption for active mode (P_{ative}) is calculated with extracting the relationship between power consumption and its manufacturing parameters (e.g., feed rate (f), spindle speed (S), and cutting depth (C)) as below:

$$P_{active} = f_1(f, S, C). \qquad \text{(Eq. 3)}$$

The active time is calculated [38] as below:

$$t_{active} = \frac{L \times St_{num}}{f \times S}, \qquad \text{(Eq. 4)}$$

where L is length to be machined. St_{num} denotes the number of stroke (one tool path for linear/circular interpolation), which can be estimated as below:

$$St_{num.} = \lceil \frac{d + t_{offset}}{C} \rceil, \qquad \text{(Eq. 5)}$$

where d is the total cutting depth and t_{offset} denotes the tolerance offset that is required to reduce the radial run-out stroke.

Energy consumption for idle is calculated as below:

$$E_{idle} = P_{idle} \times t_{idle}. \qquad \text{(Eq. 6)}$$

The power consumption for idle (P_{idle}) can be assumed as a constant value and obtained by the direct measurement, which will be given in Section 4.2. The idle time (t_{idle}) will be calculated as below:

$$t_{idle} = t_{attract} + t_{rapid} \times St_{num.} + t_{retract}, \qquad \text{(Eq. 7)}$$

where $t_{attract}$, t_{rapid}, and $t_{retract}$ denote time for attract, rapid movement for a back path, and retract in seconds. Those values are given in data collection phase.

NO₂ emission: the NO_2 emission is generated during active mode. The abstractive model for the total NO_2 emission (EM_{NO2}) is a function of NO_2 emission rate f_2( ) with three variables (f, S, C) and time for active mode (t_{active}) as below:

$$EM_{NO2} = f_2(f, S, C) \times t_{active}, \qquad \text{(Eq. 8)}$$

where the function '$f_2(f, S, C)$' will be shown in Section 4.3 and the t_{active} is known in Eq. 4.

Sustainability single score: the sustainability single score of Eco-indicator 99 (SS_{EI}) can be estimated by summation of characterization factor for energy (CF_{Energy}) by total energy consumption (E_{total}) and characterization factor for NO_2 (CF_{NO2}) by total NO_2 emission (EM_{NO2}) as below:

$$SS_{EI} = CF_{Energy} \times E_{total} + CF_{NO2} \times EM_{NO2} \ . \qquad \text{(Eq. 9)}$$

From the assessment analysis, the sustainability single score is obtained. Assessment function is performed with respect to the decision variables as below:

$$assess(SS_{EI}) = assess(CF_{Energy} \times E_{total} + CF_{NO2} \times EM_{NO2}) \ . \qquad \text{(Eq. 10)}$$

For optimization, the objective function is to minimize the sustainability single score, which corresponds to the optimal manufacturing parameters.

$$min(SS_{EI}) = min(CF_{Energy} \times E_{total} + CF_{NO2} \times EM_{NO2}) \ . \qquad \text{(Eq. 11)}$$

4.2 Data Collection phase

Data collection plan: To develop a data collection plan, we used Box-Behnken method [39] to establish the relationships between the decision variables and the output variables. We ran fifteen trials to derive the full quadratic regression models (see below) for predicting energy consumption and NO_2 emission. The first 13 trials have different input values. Trials 14 and 15 are performed to check the repeatability of the experimental conditions. Wireless sensors are installed for measuring power and air emissions.

Table 1. Measurement results with respect to feedrate, spindle speed, and cutting depth.

Trial number	Cutting parameters			Sustainability indicator of interest (SIOI)		
	Feedrate	Spindle speed	Cutting depth	Total energy consumption	Air emission (NO_2)	
Units	mm/rev	rpm	mm	kJ	ppm	mg
1	0.23	955	2.5	241.304	0.41	2.49
2	0.23	1590	2.5	204.181	0.49	2.98
3	0.27	955	2.5	206.729	0.42	2.55
4	0.27	1590	2.5	198.872	0.47	2.86
5	0.23	1273	2	231.656	0.39	2.37
6	0.23	1273	3	200.013	0.39	2.37
7	0.27	1273	2	212.249	0.38	2.31
8	0.27	1273	3	186.070	0.42	2.55
9	0.25	955	2	233.523	0.31	1.88
10	0.25	955	3	208.797	0.30	1.82
11	0.25	1590	2	213.740	0.42	2.55
12	0.25	1590	3	189.486	0.41	2.49
13	0.25	1273	2.5	209.810	0.38	2.31
14	0.25	1273	2.5	211.165	0.38	2.31
15	0.25	1273	2.5	209.067	0.38	2.31

Data collecting: Table 1 shows the results of those 15 trials. As indicated, the inputs for the first 13 trials differ. Trials 14 and 15 repeat the inputs from trial 13. Note the variability in the outputs given those same inputs. Energy consumption is measured in unit kJ, and NO_2 emission in unit ppm, respectively. In case of NO_2 emission, the concentration unit of ppm needs to be converted to the mass unit of mg/mm^3, which is required by Eco-indicator. So, 99. 1 ppm equals to 2.03 mg/m^3 in a temperature of 25˚C. Thus, the ppm unit can be converted to the mg unit, assuming that the machine room of 3 m^3 is sealed.

Table 2 shows the data relevant to times for setup, idle and teardown as well as powers for setup and teardown.

Table 2. Measurement data for generating the mathematical model.

	Machining mode		Units	Turning
Time	Setup		s	30
	Idle	Rapid movement	s	3
		Retract	s	3
		Attract	s	9
	Teardown		s	30
Power	Setup		kJ/s	0.4
	Idle		kJ/s	1.3
	Teardown		kJ/s	0.4

Determination of characterization factors: the characterization factors are used to calculate the final sustainability single score, which is expressed in Points (Pt) or milli-Points (mPt). The characterization factors are adopted from Eco-indicator 99, and Ecoinvent v2.1 to replace the normalization and weighting factors. Table 3 shows the characterization factors for environmental impacts of energy consumption and NO_2 emission. Total impact for each are specified for the eleven impact categories.

Table 3. Characterization factors for environmental impact of energy and NO_2

Impact category	Unit	Energy [kJ]	NO_2 [mg]
Fossil fuels	Pt	3.83×10^{-8}	-
Minerals	Pt	-	-
Land Use	Pt	-	-
Acidification/Eutrophication	Pt	3.71×10^{-9}	4.6×10^{-9}
Ecotoxicity	Pt	3.2×10^{-10}	-
Ozone layer	Pt	1.4×10^{-15}	-
Radiation	Pt	-	-
Climate change	Pt	2.37×10^{-8}	-
Resp. inorganics	Pt	7.58×10^{-8}	4.66×10^{-8}
Resp. organics	Pt	1.37×10^{-10}	-
Carcinogens	Pt	1.02×10^{-9}	-
Total	Pt	1.43×10^{-7}	5.12×10^{-8}

4.3 Model generation phase

Manufacturing process modeling: Figure 11 illustrates the information flows, inputs and outputs of a process model for the turning process. The setup process only consumes energy from technosphere II. The idle process consumes energy from technosphere II. The active process consumes energy from technosphere II and emits NO_2 to ecosphere. The teardown process consumes energy from technosphere II and finishes the process.

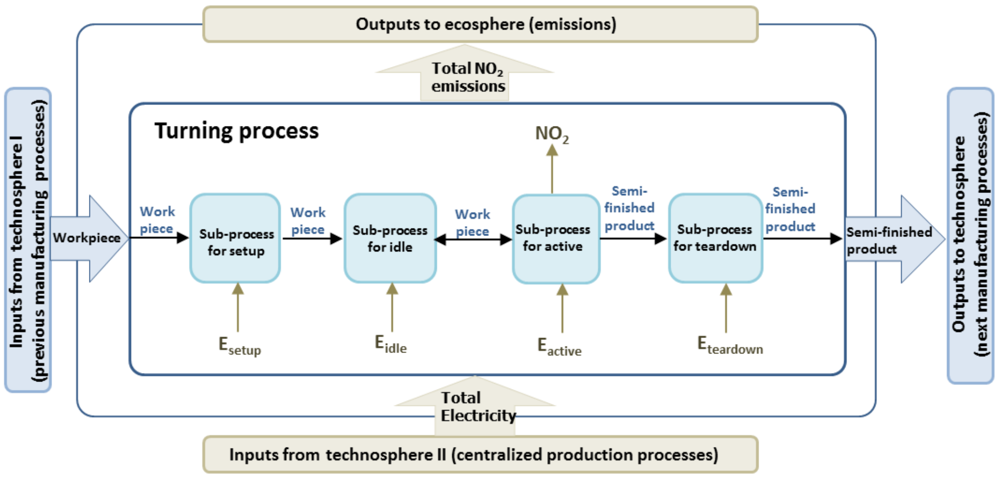

Figure 11. A turning process consisting of four sub-processes.

Analytics modeling:

Estimation of active power and NO_2 emission rate: Table 4 presents the power consumption for the four sub-processes and NO_2 emission rate. The constant setup, idle, and teardown power are given in Table 2, and the idle time is obtained by Eq. 7. The active power can be calculating by dividing the active energy consumption by the active time using Eq. 2. The NO_2 emission rate is the total NO_2 emission divided by the active time.

Table 4. The power consumption for the four processes and air emission rate.

Trial number	Energy consumption									Air emission	
	Total Energy consumption	Setup		Idle		Active		Teardown		Active	Active
		Power	Time	Power	Time	Power	Time	Power	Time	Total NO_2 emission	NO_2 rate
	kJ	kJ/s	s	kJ/s	s	kJ/s	s	kJ/s	s	mg	µg/s
1	241.304	0.4	30	1.3	30	2.2018246	80.98	0.4	30	2.49	30.75
2	204.181	0.4	30	1.3	30	3.1963008	44.17	0.4	30	2.98	67.47
3	206.729	0.4	30	1.3	30	2.11553	67.94	0.4	30	2.55	37.53
4	198.872	0.4	30	1.3	30	3.8144987	35.62	0.4	30	2.86	80.29
5	231.656	0.4	30	1.3	33	2.542927	64.79	0.4	30	2.37	36.58
6	200.013	0.4	30	1.3	27	2.7711458	50.85	0.4	30	2.37	46.61
7	212.249	0.4	30	1.3	33	2.7270003	53.30	0.4	30	2.31	43.34
8	186.070	0.4	30	1.3	27	3.0426565	41.73	0.4	30	2.55	61.11
9	233.523	0.4	30	1.3	33	2.0174752	82.59	0.4	30	1.88	22.76
10	208.797	0.4	30	1.3	27	2.3273759	64.32	0.4	30	1.82	28.30
11	213.740	0.4	30	1.3	33	3.3289445	44.11	0.4	30	2.55	57.81
12	189.486	0.4	30	1.3	27	3.7338581	34.92	0.4	30	2.49	71.31
13	209.810	0.4	30	1.3	30	2.8011839	52.41	0.4	30	2.31	44.08
14	211.165	0.4	30	1.3	30	2.8367855	52.23	0.4	30	2.31	44.23
15	209.067	0.4	30	1.3	30	2.7827645	52.49	0.4	30	2.31	44.01

Regression models: a full quadratic regression method is used to create the predictive models for active power (P_{active}, kJ/s) and NO_2 emission rate (µg/s). The active power (P_{active}) and NO_2 emission rate are dependent variables (y), while feedrate, spindle speed, and cutting depth are independent variables (X_1, X_2 and X_3). The X_1, X_2 and X_3 are substituted to x_1, x_2 and x_3 for normalizing the regression coefficients, where $x_1=(X_1-0.25)/0.02$, $x_2=(X_2-1273)/317$ and $x_3=(X_3-2.5)/0.5$. The regression model is shown in Eq. 12. Table 5 shows the sets of coefficients of the two regression models.

$$y = a + bx_1 + cx_2 + dx_3 + ex_1^2 + fx_2^2 + gx_3^2 + hx_1 \times x_2 + ix_1 \times x_3 + jx_2 \times x_3 + \epsilon \quad . \qquad \text{(Eq. 12)}$$

Table 5. Estimated regression coefficients for P_{active} (kJ) and NO_2 emission rate (µg/s).

Function term	Term	Coefficient	P_{active} (kJ/s)	NO_2 (µg /s)
	Constant	a	2.8081	44.1848
x_1	f	b	0.1239	5.4860
x_2	S	c	0.6755	19.3304
x_3	C	d	0.1573	5.8579
x_1^2	f^2	e	-0.0279	5.5092
x_2^2	S^2	f	0.0530	3.6377
x_3^2	C^2	g	-0.0081	-2.7058
$x_1 \times x_2$	$f \times S$	h	0.1760	2.2564
$x_1 \times x_3$	$f \times C$	i	0.0220	1.9350
$x_2 \times x_3$	$S \times C$	j	0.0240	1.9868

SPAF modeling of the turning process: based on SPAF syntax and semantics [29], the SPAF model that consists of context, flow, flow aggregator and process is generated for sustainability analysis including assessment and optimization. The "context" is composed of overall information (e.g., the total cutting depth and length to be machined), which can be used by other model components. The "flow" is related to the inputs and outputs of the process. The workpiece is regarded as an input flow from technosphere I, and the machined part is an output flow to technosphere. The total energy consumption is an input flow from technosphere II and the NO_2 emission is an output flow to ecosphere. The "flow aggregator" is used to summate the energy consumptions. The final SPAF model contains models for the main process and the sub-processes.

4.4 Sustainability performance analysis phase

The generated SPAF model is translated into the specific tools for sustainability analysis. For what-if analysis, SimaPro software [35] is used for the sustainability assessment. For optimization analysis, IBM ILOG CPLEX [40] is used to derive the optimal manufacturing parameters.

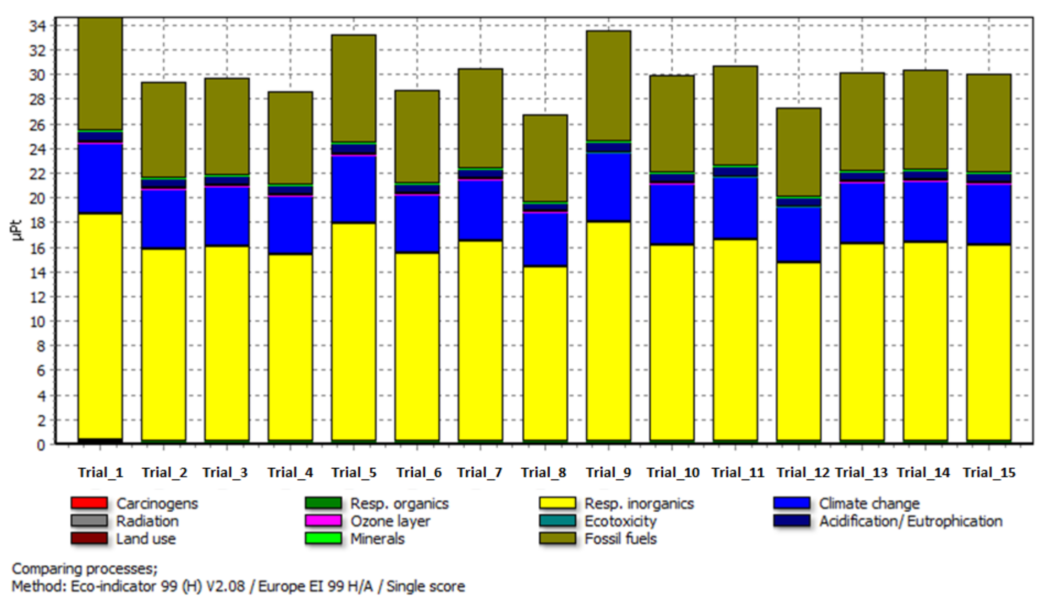

Figure 12. Results from the LCA software tool.

What-if analysis (Assessment): Figure 12 presents the bar graph of the assessment results from SimaPro model execution. Trial 1 is the worst case; it has the highest value (34.6 µPt). Trial 12 is the best case; it has the lowest value (27.2 µPt). The analysis shows that the sustainability impact (µPt) is significantly affected by the energy consumption rather than NO_2 emissions. Statistically, the energy consumption dominates over average 99.83%, whereas the NO_2 emission takes less than 0.2%.

Optimization analysis: the result from what-if analysis does not provide an optimal process parameter set. An optimization analysis is performed to provide the best parameter set. The SPAF model is translated into an optimization model in Optimization Programming Language (OPL) format, which consists of model and data files. The transformed model is executed using IBM ILOG CPLEX Optimization Studio. Specifically, Constraint Programming (CP) solver in the CPLEX optimizer is used for deriving the optimal parameter set. Figure 13 is a sample of the OPL model code for the constraint of cutting depth (line 68), the single sustainability score equation (line 112), and the objective 'minimize' function (line 118).

```
 ......
68   dvar int Depth_Cut[Orders] in Min_Depth_Cut .. Max_Depth_Cut;
      ......
112 dexpr float Sustainability [o in Orders]
        = C_E_Total*totalEnergy[o] + C_N_Total*totalNO2[o];
......
118  minimize sum(o in Orders) Sustainability[o];
```

Figure 13. Example codes in an OPL model.

Results extraction: Table 6 shows the optimal process parameter set and its corresponding result derived from the solver.

Table 6. Optimal manufacturing parameters.

Contents	Sub-contents	Unit	Value
Optimal manufacturing parameters	Feedrate	mm/rev	0.27
	Spindle speed	rpm	955
	Cutting depth	mm	2.6
Stoke	Number	-	6
Time	Setup	s	30
	Idle	s	27
	Active	s	55.846
	Teardown	s	30
Energy	Setup	kJ	12
	Idle	kJ	35.1
	Active	kJ	119.18
	Teardown	kJ	12
	Total	kJ	178.28
Power	Active	kJ/s	2.134
Sustainability	Single score	µPt	25.603

4.5 Interpretation phase

Identification of significant issues: We can identify three significant issues from these results: model accuracy for the active power and the NO_2 emission rate, consistency between assessment results and optimization tools, and, adaptation capabilities to the dynamic manufacturing environment.

Identification of types and sources of uncertainties: for the first issue, model validations for the active power and the NO_2 emission rate are necessary, since uncertainties can arise during the data fitting to the quadratic regression models. Specifically, the estimated data from the mathematical model is compared with the measured data. For the second issue, each result from the assessment and the optimization tools needs to compared for result consistency, since errors can be generated from the different usages of unit system (e.g., kJ/s and kW) and factors. For the third issue, adaptation capabilities are required to tune parameters in manufacturing processes, since the dynamic manufacturing environment usually generates the different manufacturing conditions that lead to uncertainties.

Investigation with interpreting modules:

Model validation for active power and NO_2 emission rate: the Normal Root Mean Square Error (NRMSE) is used to determine data accuracy. The coefficient of determination, denoted R^2, is used for quantifying how well measured data fits the quadratic regression model. Eq. 13 is the NRMSE function to calculate an error term of measured data ($X_{measured,\ i}$) and the predicted data ($X_{predicted,\ i}$), where a lower value indicates a better accuracy. Eq. 14 is the coefficient of determination, where a higher value indicates a better fitting. Table 7 shows the results of NRMSE and R^2 calculation. From the results, it is interpreted that the predictive models are generated accurately.

$$NRMSE = \frac{1}{\overline{X}_{measured}} \sqrt{\frac{\sum_{i=1}^{n}(X_{measured,i} - X_{predicted,i})^2}{n}} \quad , \qquad \text{(Eq. 13)}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(X_{measured,i} - X_{predicted,i})^2}{\sum_{i=1}^{n}(X_{measured,i} - \overline{X}_{measured,i})^2} \quad , \qquad \text{(Eq. 14)}$$

Table 7. Validation of the predictive models for active power and NO_2 emission rate.

Error metrics	P_{active}	NO_2 emission rate
NRMSE	0.7104 %	2.1968 %
R^2	99.74 %	99.86 %

Validation between two applications: consistency is validated by checking whether the sustainability single score from IBM CPLEX is the same with that of SimaPro. In the case of the optimal process parameter set (feedrate = 0.27 mm/rev, spindle speed = 955 rpm, and cutting depth = 2.6 mm), the score from IBM CPLEX is given to 25.603 µPt, and the score from SimaPro is assigned to 25.6 µPt. Based on this validation result, we believe that the two applications are consistent with respect to the metrics, indicators, models, data, and the results.

Table 8. Sustainability single score and its optimal manufacturing parameters according to the different manufacturing inputs.

Manufacturing inputs		Sustainability	Optimal manufacturing parameters		
Total cutting depth (mm)	Length cut (mm)	Eco-indicator 99 (µPt)	Cutting depth (mm)	Spindle speed (rpm)	Feed rate (mm/rev)
15 mm	40 mm	25.603	2.6	955	0.27
10 mm	30 mm	15.912	2.6	955	0.27
10 mm	40 mm	18.770	2.6	955	0.27
10 mm	60 mm	24.487	2.6	955	0.27
15 mm	30 mm	21.315	2.6	955	0.27
15 mm	50 mm	29.891	2.6	955	0.27
20 mm	30mm	24.638	2.9	955	0.27
20 mm	40 mm	29.848	2.9	955	0.27
20 mm	50 mm	35.506	2.9	955	0.27
19 mm	40 mm	29.578	2.8	955	0.27
22 mm	40 mm	33.075	2.8	955	0.27

Parameter calibration: Table 8 shows the result of optimal process parameter sets and their single scores corresponding to the changes of geometric properties of the workpiece. Within the optimal process parameter set, only cutting depth is changed, while the other two parameters stay the same. The result implies that cutting depth is a dominant factor that affects the geometric changes.

4.6 Decision support and guidance phase

Table 6 shows the results of sustainability single score and its optimal manufacturing parameters based on the given manufacturing condition. The results from the sustainability performance analysis phase are interpreted by performing the two validations and parameter calibration. Decision support, guidance, and actionable recommendations are given in Table 8.

5. CONCLUSION AND FUTURE WORK

In this paper, we proposed a decision guidance framework to address the limitations of LCA methods. It consists of six phases: goal and scope definition, data collection, model generation, sustainability performance analysis, interpretation, and decision support and guidance. The decision support and guidance are conducted in an incremental and iterative manner; and, each phase can be revisited or reexamined several times to reduce the uncertainties. In addition, the framework provides a unified modeling and analysis environment that help resolve the interoperability issues among different analysis applications. The framework also supports modular, reusable, extensible modeling and analysis, which leads to the reduction of time and effort for sustainability analysis.

We also demonstrated the feasibility of the framework based on a case study using a turning process. We believe such a framework can facilitate more the use of more accurate assessments which can lead to improve sustainability for manufacturing processes.

In the near future, we plan to develop a reference architecture and a prototype system based on the proposed framework. In addition, a translator will be developed to automatically transform the generated models into a standard or specific model format for sustainability analysis.

Disclaimer

Certain company names or commercial products may have been identified in this paper. Such identification was used only for demonstration purposes. This use does not imply approval nor endorsement by NIST. Furthermore, it does not imply that such company names and products are necessarily the best for the purpose.

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