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REGULAR PAPER

System Modelling for Collecting Life Cycle Inventory (LCI) Data in MSMEs Using a Conceptual Model for Smart Manufacturing Systems (SMSs)

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Abstract

Environmental concerns, economic benefits, and government legislations are forcing industries to improve their environmental performance. Life Cycle Assessment (LCA) is a tool to assess environmental impacts associated with a product, process, or service and is widely accepted in industry and academia. However, challenges to adopting LCA in the industry include complexity, expertise, efforts, and costs involved in Life cycle inventory (LCI) data collection. Micro, Small, and Medium-sized Enterprises (MSMEs) find this even more challenging. In this study, we expanded and used a conceptual model for Smart Manufacturing Systems (SMS model) to address the challenges of data collection in a shoe-making factory. The model maps each element of the factory in detail, while LCA provides the guidelines about which pieces of data help perform LCA. The data collected was used to model the foreground system, while data from the ecoinvent 3.7 database was used to model the background systems. Then, LCA was performed on a packaged pair of shoes (functional unit) using the open LCA software for two scenarios: (1) foreground system modelling without SMS model; (2) foreground system modelling with SMS model. The results using the ReCiPe 2016 midpoint impact assessment method and uncertainty analysis using Monte Carlo simulations showed significant differences in environmental impacts in most categories that pointed to the usefulness of using the proposed modelling approach for LCI data collection.

Keywords Sustainability · LCA · Data collection · Sustainable manufacturing

1 Introduction

Manufacturing is the mainstay of the modern economy and job creation [1, 2], but it creates a huge environmental burden. Manufacturing is essentially a value creation process but can potentially destroy environmental value [3]. Value creation in manufacturing happens through the transformation of materials into goods; reduction in environmental value can happen through the exploitation of resources (man, material, energy) and the generation of waste streams. Modern manufacturing is spanned across the world through a network of manufacturing organizations (OEMs, Suppliers, Transporters, Distributors, and Customers). It, therefore, creates value in various forms (employment, profits, etc.) across the world while also creating environmental impacts locally, regionally, and globally. The manufacturing industry consumes resources (material and energy), directly and indirectly, and releases large amounts of emissions, effluents, and solid waste to the environment [4, 5]. In addition, shorter product lifecycles, lower costs of products, and increased human desires have fueled the consumption rate of products, which has substantially affected the environmental performance of manufacturing. After their shorter life cycles, these wastes often end in landfills or are recycled, and considering sustainability, neither is a suitable option after a shorter life. Consumption of resources and waste generation affects the environment, incurs high costs (carbon taxes, waste treatment costs, etc.) and puts an organization's image at stake. To address this, the concept of Sustainable production [6] was introduced, which means that products are designed, produced, distributed, used,

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and disposed of with minimal (or no) environmental and occupational health damages and with minimal use of resources (materials and energy). Subsequently, organizations started working towards improving the environmental performance of their manufacturing [7, 8] due to stringent government regulations, customer preference for eco-friendly products, increased rate of resource depletion, energy-intensive material extraction from ores [9], and realization of economic benefits. Formally, the concept of sustainable production is brought into practice by the recent advent of sustainable manufacturing. Sustainable manufacturing emerges as a manufacturing concept that can holistically address all the issues related to the sustainability of manufacturing and help fulfill the goals of sustainable production and, thereby, sustainable development. Sustainable manufacturing aims at making manufacturing processes sustainable as well as making sustainable products. Sustainable manufacturing is defined as creating manufactured products that use processes that minimize negative environmental impacts, conserve energy and natural resources, and be safe for consumers, communities, and economically sound [10]. There will always be impacts associated with any manufacturing activity, which can be represented by the IPAT equation [11] below. With increase in population and affluence across the world, current technologies need to be much more efficient. Therefore, any chance of improvement in eco-efficiency should be utilized and alternative choices must be evaluated, compared and, these if perform better, must be selected.

$$I = P \times A \times T$$

where I is the impact (e.g., climate change), P is the population (global, regional, local), A is the affluence per capita (e.g., GDP/person), and T is the technology factor (impact per delivered service, e.g., kg CO_2/rupee).

The first step in addressing sustainability issues in a system is to know its current state and then compare it with the other systems for any changeovers. Various sustainable assessment methodologies, indices, and toolkits are available for assessing the sustainability performance of products and systems. Each methodology has its way of measuring sustainability performance. Some address a product's four life cycle stages (Pre-Manufacturing, Manufacturing, Use, and Post Use), while others address only a few of these. Some are meant for business sustainability and organizational sustainability only. Some address all three stages of the Triple bottom line (Economy, Environment, Society), while others address only one or two out of these. The structure (categories, subcategories, etc.), data requirement, and data analysis of these methods also vary [12]. Life Cycle Assessment (LCA) is essential to this transition, which allows organizations to quantify potential environmental impacts associated with their products, processes, and services [6]. LCA is a method for quantitatively assessing a broad range of environmental aspects and potential impacts associated with a product, process, or service by taking a life cycle perspective from raw material acquisition through production (cradle to gate), use, end-of-life recovery, and disposal (cradle to grave) [13, 14]. LCA has been able to bring the expertise from several domains and has categorized the impacts in terms of their effects within local, regional, and global boundaries. LCA helps translate manufacturing data to various environmental impact categories using structured and well-documented pathways. LCA has a wide range of applications: it can support governments in policy formulation, implementation, and evaluation [15], industry in product and process development, marketing, supplier selection, etc. [16–18] and consumers through product labeling [19].

The effectiveness of LCA lies in the quality of Life Cycle Inventory Analysis (LCIA), which includes the identification and quantification of inputs, outputs, and wastes associated with the product system [13, 14, 20]. The collection of such data is the most time and resource-consuming part of LCA [21] and is a significant hurdle in implementing LCA. This has also led to the development of Life Cycle Inventory databases like ecoinvent 3.7 [22], Gabi [23], Exiobase [24], ELCD [25], US-NREL [26], etc. These databases can provide inventory data on various products and services needed for LCA applications, such as raw materials, electricity generation, transport processes, and waste services [27]. However, there are many issues associated with the use of inventory databases. One is the high cost of the database, which is a hurdle for most MSMEs [19]; the other is the lack of consideration of variations in operating conditions, production rates, consumption by peripherals, work environment, etc. [4, 27, 28]. Besides, MSMEs have further barriers to implementing LCA, the need for changes in workplace routines, the perceived complexity of the LCA methodology, and the shortage of qualified personnel to carry out an LCA. Today, modern industry recognizes the importance of including sustainability in is factory operations [28], which can be done by adding sustainability assessment modules and dashboards to its information systems. LCA is widely used in industry. The critical issue faced while performing LCA in manufacturing is its lack of suitability to translate environmental impacts to manufacturing processes on the shop floor. It requires data from the factory floor to be clearly and readily available to perform LCA. Therefore, to have a simplified, improved, and faster process of data collection for LCIA, there is a need for modelling foreground systems in detail beforehand with clear mapping of parts, processes, and manufacturing systems and data requirements guided by LCA.

Based on the gaps, the following research questions have been formulated:

1) How to map data from a foreground system (Manufacturing System) to perform LCA?
2) Which manufacturing system elements are the data sources required to perform LCA?
3) What difference in environmental impacts does it make if we model a detailed foreground system?

The paper has been organized into different sections to answer the above questions. Section 2 addresses the literature on LCA methodology and manufacturing system representations. Section 3 presents the methodology for the LCI data collection and the data collected. Section 4 shows the Environmental impact results. Finally, Sects. 5, 6 and 7 present discussion, conclusions, and scope of future work.

2 *Literature Review*

2.1 LCA Methodology

LCA aims to assess and address the environmental impacts associated with the product or system of interest, both manufactured and consumed. It is a tool to quantify and compare the eco-efficiency of alternatives. It does not directly compare two alternatives A and B; it compares two ways (using A and B) of achieving the same functional unit. A functional unit [14] is a precise and quantified measure relating the function to the inputs and outputs to be studied. Functional units should relate to the product/process/service functions rather than the alternative itself (e.g., using pair of hands cleaned per day rather than using the number of tissues used). Various organizations and regulatory bodies have made efforts to facilitate the applications of LCA and life cycle thinking. ISO 14040/44 standards provide a framework and principles for LCA. The ILCD handbook [29] supports the consistency and quality of LCA as the ISO framework leaves the individual practitioner with a range of choices that can change the results and conclusions of an assessment. The ILCD Handbook is technical documentation that guides good practice in Life Cycle Assessment in business and government. UNEP-SETAC launched a program called ‘Life Cycle Initiative’; the purpose was to enable users worldwide to put life cycle thinking into effective practice [30]. EPLCA-JRC is the E.U.‘s knowledge base to support business and policy needs for LCA [31]. As mentioned earlier, several inventory databases have been developed to support the inventory part of LCA, which cover many industrial sectors and aim for consistent data standards and quality [19]. Impact assessment is performed using the inventory data from the databases and other sources. There has been continued development of impact assessment methods that are quantitative and science-based, like CML 92, EcoIndicator99, Recipe, Impact2002+, etc., to quantify all the environmental impacts [32]. These methods cover various impact categories, damage categories, and areas of protection. The development has led to the extensive application of LCA in product development/improvement, product marketing, supplier selection, strategic planning, policy formulation, implementation, and evaluation.

According to ISO 14,040/44, there are four (iterative) phases in an LCA study:

a. The goal and scope definition phase,
b. The inventory analysis phase,
c. The impact assessment phase, and
d. The interpretation phase.

After setting the initial goal and scope, the accuracy of LCA results depend on the quality and detail of Life Cycle Inventory data. LCI databases like ecoinvent 3.7 provide data for products and services as an average, like the amount of energy consumed for processing 1Kg of aluminum. Though these databases thoroughly review any new data entry and constantly update the databases [33] but still fail to address certain issues. Issues like the shape of the part (geometry) significantly affect the energy used and material wasted for making a same-weight part with different geometries [34]. Apart from this issue, manufacturing system-level variations can lead to different environmental impacts for similar products made at different times of the day or in different lots. This can be due to variable energy mix during the day, waiting times, bottlenecks, etc., in the manufacturing line [35]. In order to address such issues, data from the foreground system, in this case, a manufacturing system, must be collected as primary data. Still, the complexity of inventory analysis and data structure can discourage the widespread use of LCA, not fully exploiting its benefits [36].

The literature suggested that Mapping data from manufacturing systems is one of the major requirements of the study; hence we reviewed multiple manufacturing process and system representation methods. There have been continuous efforts in modelling manufacturing systems for many years, and multiple methods have come up over time. The significant contribution started from Hubka’s Technical System model [37]. The model at an abstract level covers technical process, system, Humans, Feedback and interactions, and transformation of material, energy, and information using three kinds of systems (execution, information, and management) that operate in active and reactive environments bounded by space and time. Specific to LCA, CO_2PE! initiative developed the UPLCI framework [38] to store manufacturing specific LCI information for environmental analysis using a screening and in-depth analysis. The framework has acted as a foundation for future sustainability-related characterization of manufacturing processes. UPLCI for the metal injection molding (MIM) process has been recently demonstrated using an example case study for a sequence of processes and shows the versatile nature of UPLCI models [39]. Standards like ASTM E2986-18 [40] and ASTM E3012-20 [41] have tried to standardize sustainability-related manufacturing process data and have served as the backbone of any sustainability characterization of manufacturing processes. Recent advancement in this area [42] shows how to reuse and extend existing information models of manufacturing processes by modelling a Milling process. Most of these models are incremental in their nature and reinforce each other. The focus of most approaches is either on modelling a single manufacturing process/machine or systems. The models seem to offer less advice on potential modes and methods for data characterization. There is still a significant amount of detail that's needed to be worked out in these standards/models to have an unambiguous map of the manufacturing processes and systems. The proposed conceptual model for Smart Manufacturing Systems (SMS model) [43] first views and captures the details at the manufacturing systems operations and supply level and then at the process/activity level. SMS model also presents a way to create a model of a complete manufacturing system with specific System characteristics and as a network of connected processes. The system and process elements are defined to reduce complexity and ambiguity for non-expert data users. The SMS model presents a domain agnostic process model where specialized knowledge of each manufacturing process is not a prerequisite for characterizing the process.

2.2 Smart Manufacturing System Model

A conceptual model for Smart Manufacturing Systems (SMSs) is expanded and used to model the factory; the model facilitates identifying and collecting inventory data. The model first views and captures the details at the manufacturing systems level and then at the process/activity level. The model tries to capture information about the type of products manufactured, complexity of the manufacturing system, manufacturing system type, automation level, building services, inventory and production control strategies, and waste segregation and disposal strategies at the manufacturing system level. At the process/activity level, the SMS has an Input-Output process model, as shown in Fig. 1. The Inputs and outputs fall under the following classes: Material Objects (MO), Energy (E), Information (I), Equipment (Eq), Human (H), and Environment (Env). The model can map the whole manufacturing system in terms of Processes/

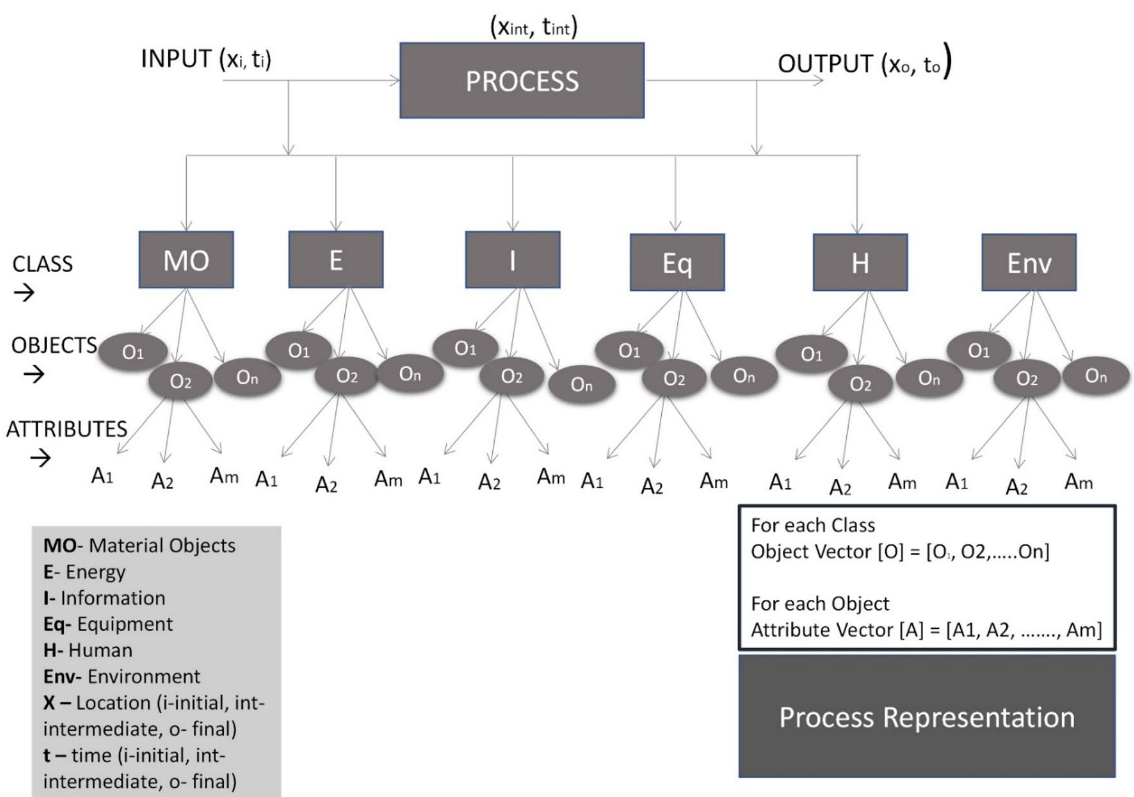

Fig. 1 Process representation in a smart manufacturing system model

Activities, location, time, and modes of operation. It can detail the Inputs and outputs (Material, energy, Information), Equipment, Humans, and Environment of/for each process/activity to the attribute level. Several Objects (O) constitute these inputs and outputs, falling under one or more of these classes. These objects are characterized by one or more attributes (A), e.g., tool-tip temperature, etc. Real-time assessment of these attributes could be critically influential for improving manufacturing systems. These attributes are also direct indicators of what needs to be measured, from where and how these could be measured.

The attributes can be identified depending on the type of study, and a plan for their measurement can be made. For performing an LCA study, we would need material, energy, waste, and emissions information. Further detail will reveal that energy is not as straightforward to measure and is not necessarily an average. It depends on many factory variables like the mode of operation, time for operation, waiting times, bottlenecks, rejections, repairs, downtimes, failures, etc. Likewise, emissions (local) will have different impacts depending on human involvement in the task. Waste is also a measure of removed material from the stock material and attributing rejects and reworks to the products made. The material here refers to the material required to make the product and the auxiliary material required to run machines (Lubricants, coolants, compressed air). There might be process limitations, but there are planning problems too at the factory floor. If not handled optimally, it can result in a higher environmental footprint of the parts made.

There is a need to model each manufacturing system as a complex system with all relevant details, and no two manufacturing systems are the same (variation among manufacturing systems based on automation, layout, work culture, etc.). If not adequately modelled, this can lead to missing crucial information and to performing incomplete or wrong assessment (in our Case, LCA). The model can help plan for both direct and indirect pieces of information that can have a role in LCA, e.g., two (A and B) similar batches of parts were made in the same factory on the same day, and yet it took a different amount of time and resources to complete each batch (more time and material for B). This can be due to bottlenecks, shortages, breakdowns, high rejections, reworks, etc. More time means more electricity consumption; more rejections mean more use of material. This reflects that Parts of Batch B will have a higher environmental footprint than A.

3 Methodology

SMS model is generic in nature and can help in collecting data for any type of performance assessment like Economic assessment, Environmental assessment etc. for Manufacturing Systems. The Performance assessment goals decide the Key Performance Indicators (KPIs), and the data required to measure those KPIs can be mapped from the factory floor using the SMS model as shown in Fig. 2. In this paper, LCA, with its Goals and scope definitions, provided the starting point for modelling the factory using the SMS model, i.e., the KPIs required to be measured and reported. This information is then used with the help of SMS model to map the key metrics at different manufacturing stations across the factory floor required to evaluate those KPIs. In an LCA study, these KPIs are Environmental impact categories. The required data for measuring those KPIs from the factory floor are material, consumption, energy consumption, waste generated, and time spent at each station. The SMS model helped in creating a detailed map for each station irrespective of who is collecting the data and hence helps in improving coverage, reducing uncertainty, and increasing the robustness of the data collection process.

The LCA methodology is used to perform the LCA of a pair of shoes by modelling its foreground manufacturing system – an orthotic shoe manufacturing and assembly factory. We modelled the LCA study using openLCA 1.10.3 software [44] to demonstrate the use and effectiveness of the model by:

a. Modelling the foreground manufacturing system without using the conceptual model for SMSs (Fig. 3).
b. Modelling the foreground manufacturing system using the conceptual model for SMSs (Fig. 3).

This study aims to assess the SMS model's effectiveness in collecting inventory data by comparing life cycle impact results. Therefore, we conducted two LCA studies for a common functional unit (a packaged pair of shoes). The data for one study is collected using the SMS model and for the other one without the model. The scope of the assessment is Cradle to Gate, as shown in Fig. 3, and is done in four phases: materials, transportation, manufacturing, and packaging. We collected data from an orthotic shoe factory (an SME) in Bengaluru, India. The factory has several mechanized and

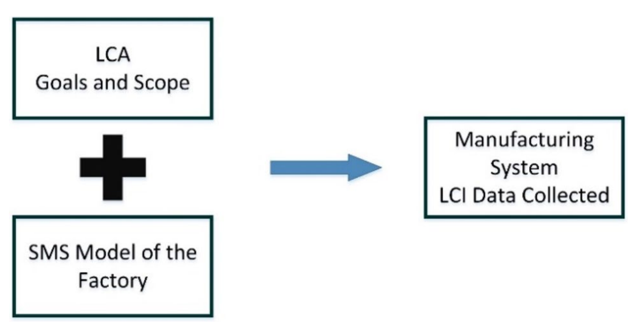

Fig. 2 Framework to represent joint LCA and SMS model

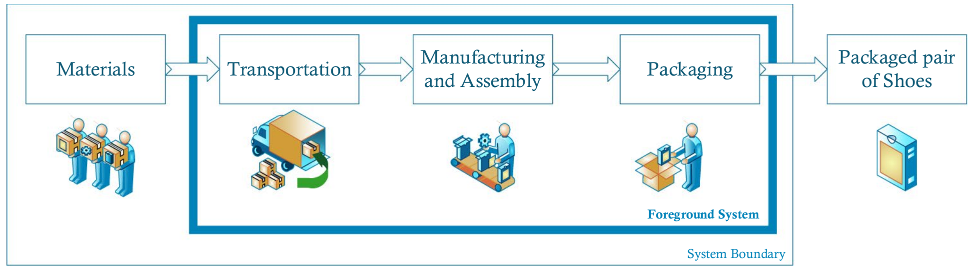

Fig. 3 System boundary representation

manual operations and makes about 250–300 pairs of shoes daily. Transportation, shoe manufacturing and assembly, and packaging are modeled as foreground systems, while resource extraction and processing comprise the background system. There were frequent visits to the factory to collect inventory data. For energy consumption, we performed time studies on how much time a part spends on a machine, and multiplying that with the machine's rated power, we estimated the energy consumption. For material consumption and waste generated for each part, we counted the number of parts generated from one sheet and weighed each part. Then weighed the sheets after cutting and divide that weight by the number of parts generated from that sheet to attribute wastage associated with each part (wastage per part). We found extensive use of adhesives and primers, and we estimated the amount of adhesives and primer used per pair of shoes to estimate VOC emissions per pair of shoes. There were three types of adhesives and one primer, and we collected data on adhesive consumption as the number of pairs produced per liter of each adhesive/primer consumed. Using this data, we calculated the amount of adhesive and primer consumed in preparing one pair of shoes, and the VOC emissions were estimated using literature [45]. Sometimes human judgements are used when collecting LCI data where some data regarding the smaller elements of the product may be ignored. The SMS model presents a clear map of processes with its inputs and outputs and does not lead to missing data based on value judgements. For instance; in the data collection for Case a, due to poor judgement of ours and the factory supervisor, it was assumed that the nylon thread used was very less and hence was neglected, but in Case b, when we detailed each process using the SMS model the real amount of thread and other smaller parts being used emerged. Inputs given by factory supervisors were used to calculate transportation distances for raw material, while the weight of raw material in each trip was calculated using data on inventory and the number of pairs of shoes manufactured per month.

Ecoinvent 3.7 inventory database [22] is used to model the background system and some elements of the foreground system. ReCiPe 2016 (Hierarchist) [46] is chosen as the Life Cycle Impact Assessment (LCIA) method in the study, as it comprehensively covers mid-point impact categories and endpoint damage categories and provides characterization factors that are representative of the global scale. LCIA translates emissions and resource extractions into a limited number of environmental impact scores through characterization factors [47]. Characterization factors indicate the environmental impact per unit of the stressor (e.g., per kg of resource used or emission released). ReCiPe 2016 calculates 18 midpoint indicators: Global warming, Stratospheric ozone depletion, Ionizing radiation, Ozone formation (Human health), Fine particulate matter formation, Ozone formation (Terrestrial ecosystems), Terrestrial acidification, Freshwater eutrophication, Marine eutrophication, Terrestrial ecotoxicity, Freshwater ecotoxicity, Marine ecotoxicity, Human carcinogenic toxicity, Human non-carcinogenic toxicity, Land use, Mineral resource scarcity, Fossil resource scarcity, Water consumption and three endpoint indicators. Midpoint indicators focus on single environmental issues, for example, climate change or acidification. Endpoint indicators show the overall environmental impact at three high aggregation levels: (1) effect on human health, (2) biodiversity, and (3) resource scarcity [48].

Pedigree matrix [49] and lognormal distribution are used to specify and reduce uncertainty. The pedigree matrix is an uncertainty quantification method with five data quality indicators, each having five score values (1 being the best and five being the worst). These five indicators are reliability, completeness, temporal correlation, geographical correlation, and further technological correlation. For each data source, the pedigree matrix is constructed by specifying scores for each indicator, and the uncertainty of the whole group is quantified in terms of geometric standard deviation (GSD). The GSD and input value are then used to create lognormal distribution [50] for the inputs to reduce uncertainty by overcoming scaling effects in the analyzed data. Further, we performed Monte Carlo simulation [51, 52] to check uncertainty in the impact results.

3.1 LCA of a Pair of Shoes: Modelling the Foreground Manufacturing System Without Using the Conceptual Model for SMSs (a)

3.1.1 LCA Overview

The goals of the study were to "Calculate Environmental impacts caused by a packaged pair of shoes" and "Compare Environmental Impacts of a packaged pair of shoes by (a) modelling the foreground manufacturing system without SMS and (b) modelling the foreground manufacturing system with SMS." A packaged pair of shoes with a total weight of 510 g was chosen as the functional unit for the LCA study. Product System and system boundary were chosen for the study by considering " Production of Raw material as the background system" and "Shoe Manufacturing and Assembly as the foreground system." The use stage of the pair of shoes was assumed to have a negligible environmental impact. The background system was modelled using EcoInvent 3.7 database in openLCA 1.10.3 software. The data for foreground system modelling was collected by observations, calculations, and meeting with the supervisor and operators at the factory floor. The data was then used to create flowcharts of the layout. ReCiPe 2016 (Hierarchist) midpoint was used as Life cycle impact assessment (LCIA) methodology for the study (Fig. 4).

3.1.2 Data Collection Model

We created a process flowchart, as shown in Fig. 5, to represent and track all the activities of the orthotic shoe factory. The flowchart gave us a good view of the processes and helped in collecting LCI data related to each process.

Fig. 4 Selected shoe model

3.1.3 Data Collected

The material and energy data collected from the factory are shown in Tables 1 and 2, respectively.

3.2 LCA of a Pair of Shoes: Modelling the Foreground Manufacturing System Using the Conceptual Model for SMSs (b)

3.2.1 LCA Overview

The goals, functional unit, product system, background system, and LCIA methodology of the study were already defined in Sect. 3.1.1. The foreground system was modelled using a conceptual model for Smart Manufacturing Systems (SMS model). The data for foreground system modelling was collected using the SMS model. The SMS model acted as a template to collect information from the factory floor through observations, calculations, and inputs from supervisors and operators at the factory floor.

3.2.2 Data Collection Model

Data was collected by referring to the LCA data requirements and using the SMS model. LCA provided guidelines about the KPIs and related metrics [19], while the model helped map those metrics to the factory floor. The model helped comprehensively model the factory, pointing to information on the type of product, complexity, classification of the manufacturing system, automation level, production control, waste disposal, manufacturing processes, and inputs and outputs. Most of the processes in the observed system are manual except for five mechanized processes. Power ratings of each machine and the time one part spends on each machine are used to calculate the energy consumed in making one shoe. It was not measured in real time because of the constraints of the factory. Uncertainty is high due to such estimations, but in this comparative study, we have used the same estimation for both cases. In addition, waste generated at each process is calculated, and its attribution to each part is done (e.g., n parts taken out from a single material sheet and left out sheet was weighed, and this weight is equally divided and attributed as waste for each of the n parts.). Sourcing of raw materials is from two places majorly (one in the northern and the other in the eastern part of the country) within the country's geographical boundaries. The transportation is by road, which on average cover around 4000 Km to reach the factory. The factory supervisor and manager verified this.

Step I: Manufacturing system-level Information

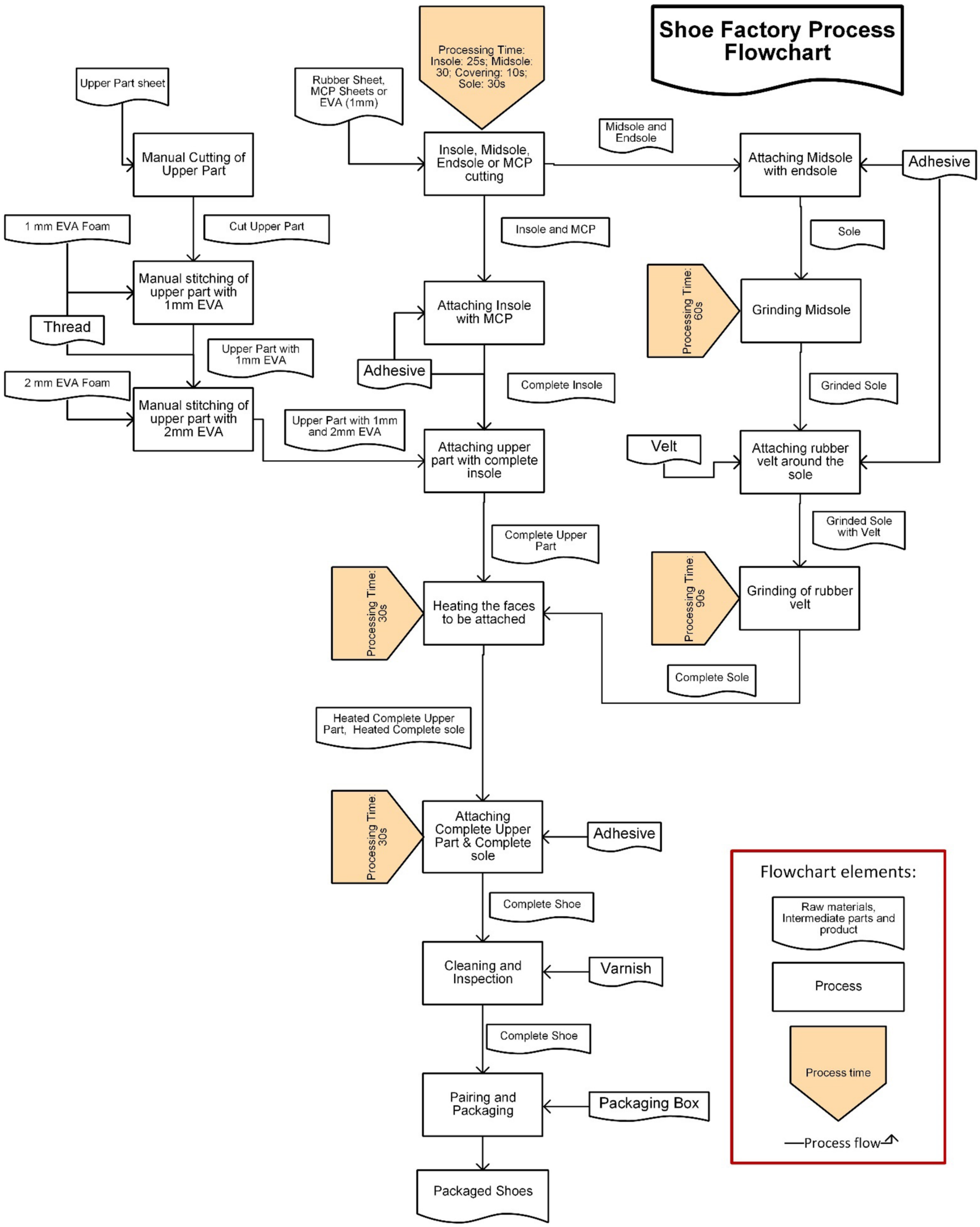

Fig. 5 Process flow of the shoe factory

Shoe factory is mapped using constructs defined in the SMS model is presented in Table 3.

Step II: Process level information

Process flow of the factory floor is created, and then details of input/outputs for each process are documented according to the SMS model and LCA requirements. The SMS model can map various information about the process and

Table 1 Material data of a single shoe

S.No.	Part/material name	Material	Weight (g)	Corresponding ecoinvent 3.7 data
1	Upper part	Brown rexine napha	30	Polyurethane, flexible foam
2	Upper part (packing)	EVA (1 mm)	5	Ethylvinylacetate, foil
3	Upper part (lining)	EVA(2 mm)	15	Ethylvinylacetate, foil
4	Velcro (2 nos)	Velcro	4	Textile, non-woven polypropylene
5	Label	Synthetic rubber	2	Synthetic rubber
6	Bottom insole	MCP (10 mm)	25	Polymer foaming
7	Insole covering	EVA (1 mm)	10	Ethylvinylacetate, foil
8	Endsole	Synthetic rubber	55	Synthetic rubber
9	Midsole	MCP	8	Polymer foaming
10	Velt	Synthetic rubber	5	Synthetic rubber
11	Packaging box	Board	150	Folding boxboard carton
12	Shoe material waste		80	Waste plastic, mixture
13	Adhesive		40	Adhesive, for metal

Table 2 Energy data of a single shoe

S.No.	Machine	Rated power (kW)	Processing time/ shoe (s)	Energy consumed per shoe (MJ)	Energy consumed per pair (MJ)
1	Die Cutting	4.3	95	0.4085	0.817
2	Grinding	4	150	0.6	1.2
3	Heating	3.5	30	0.105	0.21
4	Pressing	5	30	0.15	0.3
Total energy consumed				1.2635	2.527

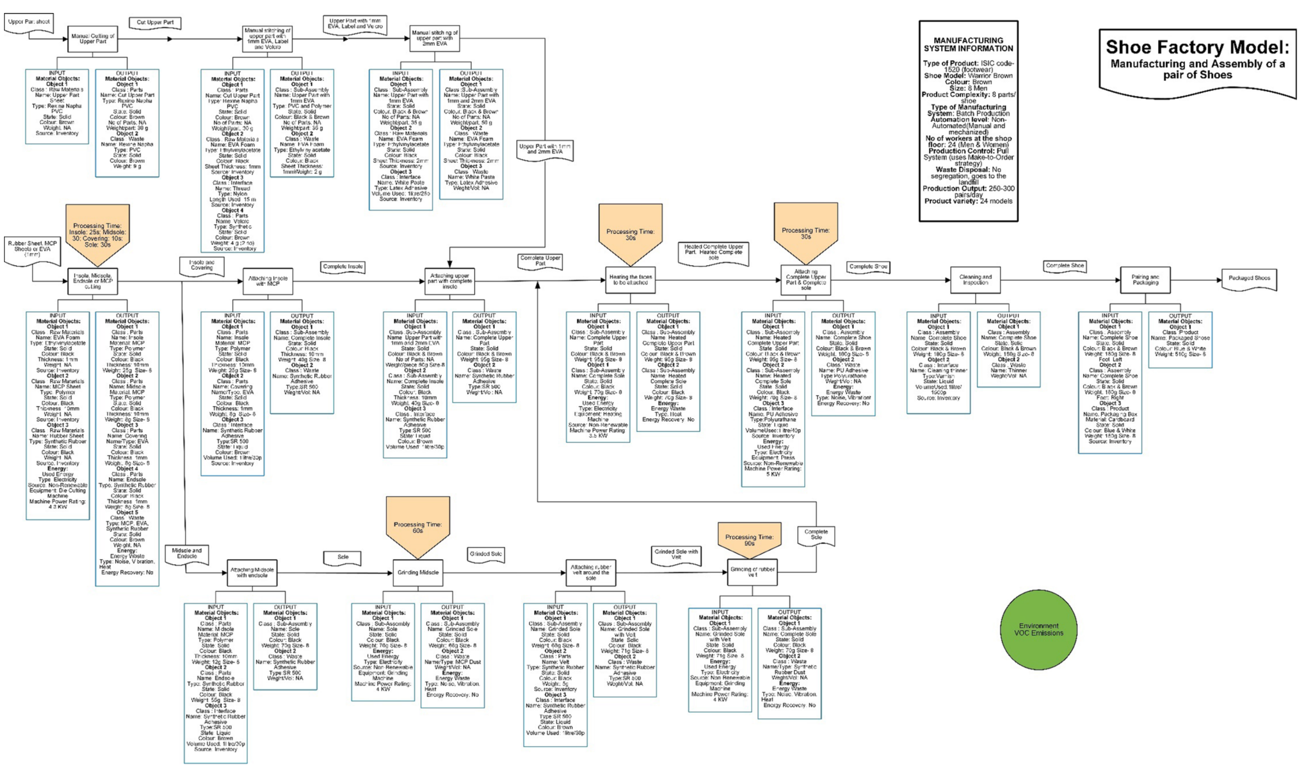

Fig. 6 Shoe factory represented using SMS model

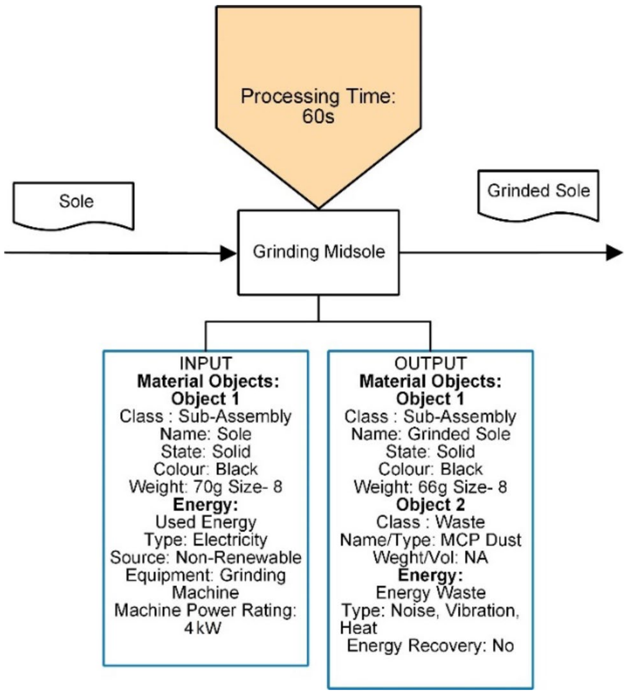

Fig. 7 Process description in detail

the factory, but not all information is relevant for performing LCA. Therefore, keeping LCA as the focus of our study, material flow, material consumption, material waste, and energy consumption are modelled. Figure 6 shows the modelling of the whole factory, with the whole manufacturing system and process information. Figure 7 is the cut-out portion of the complete factory model to show a process in detail. Some data were calculated using the measured and observed data like VOC emissions, weight of adhesives and thinner, etc., as there was no direct way to measure those data. The significant difference in collected data using the SMS model was due to the amount of detail to which it can map each process, and data that otherwise would have been neglected is considered.

3.2.3 Data Collected

The shoe is worked in two stages, the upper part, and the sole. The two parts are then assembled to form a complete shoe, then inspected, paired, packaged, and sent to the inventory. Table 4 presents the weight, attributed weight, wastes, and the materials used to make each part. Table 3 shows information about the power ratings of machines used and processing time on each machine per shoe, and this is similar for both cases. Attributed weight includes the weight of a part or material and the wastage associated with that part or material; for example, suppose n number of soles are cut-out from a rubber sheet using a die. After cutting, some material is left on the sheet, and no further soles can be cut out from that sheet, and it is a waste now. However, the used sheet doesn't form the sole but has been used to bring the sole into reality. Hence, the total weight of the left-out sheet is measured and divided by the number of soles (n) and then added to the weight of each sole to get the attributed weight. Total Product weight = 510 g Total Attributed Product Weight = 680 g.

4 Results

The inventory data collected is used to model the flows of the product system by connecting foreground and background systems in openLCA 1.10.3 software. We used Ecoinvent 3.7 database to model the background system and calculated environmental impacts using all 18 categories of the ReCiPe 2016 Mid-Points impact assessment method. Environmental LCIA of a packaged pair of shoes are presented in Table 5, showing the contribution for both (a) foreground system modelling without using the SMS model and (b) foreground system modelling using the SMS model. Table 5 also presents Impact Ratio of (a) foreground system modelling without using the SMS model and (b) with using the SMS model. This ratio was calculated to normalize the scores for comparative analysis. It shows the difference in environmental impacts between the two cases. The percentage difference for each impact category ranged from 4.39 to 50.7%, and the average difference of all 18 categories

Table 3 Manufacturing system-level information

	Factory level information
Type of products manufactured	ISIC code- 1520 (Manufacture of footwear)
Shoe model	Warrior Brown, Size- 8 Men
Complexity	8 parts and 14 processes
Classification of manufacturing system	Batch Production
Automation level	Non-automated (Manual and mechanized)
Production control	Pull system (uses Make-to-Order strategy)
Waste disposal	Only waste rubber segregated rest goes to the landfill

Table 4 Material data of a single shoe (using SMS model)

S.No.	Part/material name	Material	Weight (g)	Waste(g)	Corresponding ecoinvent 3.7 data
Complete upper part					
1	Upper part	Brown Rexine Napha	30	9	Polyurethane, flexible foam
2	Upper part (packing)	EVA (1 mm)	5	2	Ethylvinylacetate, foil
3	Upper part (lining)	EVA(2 mm)	15	5	Ethylvinylacetate, foil
4	Velcro (2 nos)	Velcro	4	N.A.	Textile, non-woven polypropylene
5	Label	Synthetic Rubber	2	N.A.	Synthetic rubber
6	White paste	Latex Adhesive	20	N.A.	Adhesive, for metal
7	Thread	Nylon	1.07	NA	Nylon 6
8	Bottom insole	MCP (10 mm)	25	8	Polymer foaming
9	Insole covering	EVA (1 mm)	10	3	Ethylvinylacetate, foil
10	Adhesive	SR500	20	N.A.	Adhesive, for metal
Complete sole					
1	Endsole	Synthetic Rubber	55	15	Synthetic rubber
2	Midsole	MCP	8	4	Polymer foaming
3	Velt	Synthetic Rubber	5	N.A.	Synthetic rubber
Complete shoe					
1	Adhesive	PU	14.625	NA	Polyurethane adhesive
2	Cleaning thinner	Halogenation Primer	3	N.A.	Acrylic varnish, without water, in 87.5% solution state
3	Packaging box	Board	150	NA	Folding boxboard carton
4	Tissue	Paper	3	N.A.	Tissue paper

Table 5 Environmental LCIA of a packaged pair of shoes

Impact category	Reference unit	Result (a)	Result (b)	Ratio (a/b)	R	C	T	G	F
Fine particulate matter formation	kg $PM_{2.5}$ eq	0.00470127	0.0053689	0.87564941	3	2	4	3	2
Fossil resource scarcity	kg oil eq	0.91970917	1.07080122	0.85889813	1	2	3	2	1
Freshwater ecotoxicity	kg 1,4-DCB	0.13492732	0.16489803	0.81824697	1	1	3	1	1
Freshwater eutrophication	kg P eq	0.00089469	0.00099296	0.90103759	1	1	4	1	1
Global warming	kg CO_2 eq	2.55307181	3.00912333	0.84844372	3	2	4	3	2
Human carcinogenic toxicity	kg 1,4-DCB	0.1586625	0.19033162	0.83361085	1	1	4	3	2
Human non-carcinogenic toxicity	kg 1,4-DCB	3.72610822	4.48992037	0.82988292	1	1	3	1	1
Ionizing radiation	kBq Co-60 eq	0.80779397	0.8448471	0.95614221	1	1	5	1	1
Land use	m^2a crop eq	0.16098968	0.1723147	0.93427713	2	3	4	3	1
Marine ecotoxicity	kg 1,4-DCB	0.1865854	0.22714288	0.82144508	1	1	3	1	1
Marine eutrophication	kg N eq	0.00016568	0.00030022	0.55187717	1	2	4	2	1
Mineral resource scarcity	kg Cu eq	0.11631586	0.12263654	0.94846007	1	3	3	1	1
Ozone formation, Human health	kg NO_X eq	0.0068932	0.00810553	0.85043143	3	2	4	3	2
Ozone formation, Terrestrial ecosystems	kg NO_X eq	0.00718888	0.00845586	0.85016622	3	2	4	3	2
Stratospheric ozone depletion	kg CFC11 eq	7.5383E-07	1.5289E-06	0.4930495	3	3	4	4	2
Terrestrial acidification	kg SO_2 eq	0.00821629	0.00958685	0.8570369	3	2	4	3	2
Terrestrial ecotoxicity	kg 1,4-DCB	9.25447446	10.7509966	0.86080154	2	2	4	3	1
Water consumption	m^3	0.05546302	0.06203474	0.89406394	3	3	4	3	2

amount to 16.76%, which is quite significant. A significance test was performed using Welch two-sample t test, and the impact difference between both cases was found to be statistically significant with a p value = 1.742e-05 and 95% confidence interval percentage: [22.74%, 10.77%]. Table 5 also shows Data quality indicators for each impact category calculated using pedigree matrix information for each input and output using R, C, T, G, and F values. R, C, T, G and

F correspond to the following data quality indicators; Reliability, Completeness, Temporal correlation, Geographical correlation, and Further technological correlation from the Pedigree Matrix. Impact Ratio = Ratio(a/b) (from Table 5).

The uncertainty of the impact results for both cases was simulated using Monte Carlo simulation in openLCA 1.10.3 software. Using lognormal input distributions and modeled over 1000 iterations [53], the uncertainty analysis illustrates in Table 6 the mean, standard deviation, 5th and 95th percentile values for each impact category and for both Cases a and b.

5 Discussion

The difference in impacts between modeling and not modeling the foreground system is well established. The literature has reported it, but minute details were left behind even when the foreground system was modeled without using the SMS model. Using the model helped include information explicitly required to perform a reliable and robust LCA. The results demonstrated the importance of having detailed information from a manufacturing system to have complete LCI data. In manufacturing activities, there are many losses, like rejections, rework, waiting times, etc., due to manufacturing operations and supply chain issues. Therefore, these must be accounted for in the LCA models. SMS model can help find these losses so that environmental impacts from the losses can be calculated and plans to reduce those can be made. The model can also help implement corrective actions once the study is completed. It can help track any changes made in the system and reflect improvements. MSMEs with limited resources can use the SMS model to create an in-house Life Cycle Inventory and perform LCA studies. These MSMEs can start with KPIs defined by LCA goal and scope definitions. Then use the SMS model to map the whole manufacturing system with information related to product category, product complexity, system complexity, control strategies, etc., and then model each manufacturing process/activity with relevant data from the factory under various classes. After completing this exercise, they will have a decent detail of LCI data.

The model can be further extended for Smart Manufacturing systems where one can use real-time data to show the changes in LCA results with varying production conditions on the shop floor, thereby helping in the formation of optimum working strategies for better environmental performance. Smart Manufacturing is leveraging IoTs, sensors, etc. for collecting Data from Machines, Processes, Humans, Environment, building services, and Supply Chains and using Cloud Computing Resources, A.I., etc., to analyze that data for specific Business cases. Data is at the heart of Smart Manufacturing, and much focus should be given to collecting the correct data. This is governed by the Business case at hand, technical feasibility, and the amount of resource one wants to put in. SMS model can help to bring together Business cases and associated KPIs to the Manufacturing System Data. Using the SMS model, the data collected is highly structured, and the context, from which machine, at which time, who was the operator, what was the tool condition, etc., is specified. Hence rather than going for a large amount of data, one can have contextual data using the SMS model, and Data-Centric A.I. (which has higher accuracy with lesser data) can be leveraged to analyze it [54]. Data-Centric A.I. is much more efficient than Model Centric A.I. as a lesser amount of computational resources are wasted in training the models [55]. This can lead to efficient Data analytics with higher accuracy and low energy consumption.

6 Conclusion

We concluded that the SMS model could guide data collection by mapping the whole factory, as shown in Fig. 1. It covers all the elements of a factory by explicitly modelling the manufacturing process/activity. It can act as a template for collecting data even by less skilled individuals with appropriate detail. Figure 6 shows a complete map of all the processes, their relationships, and their inputs and outputs; it details all the equipment, material, waste, and energy information. Hence chances of missing those pieces of information are reduced. The model usage will lead to a reduction in ambiguity and improved completeness in the data collection process. Specifically, for MSMEs, this can help in developing in-house LCA capabilities with fewer resources. With better access to data, factory, and LCA studies, the roadmap to improvement can be effectively created and implemented in-house by MSMEs. This implementation will also lead to monetary savings by not going to third-party consultants for performing LCA studies. Tables 4 and 5 highlights the difference in environmental impacts between the two cases, with percentage differences for each impact category ranging from 4.39 to 50.7%. Differences for environmental impact categories "Marine eutrophication" and "Stratospheric ozone depletion" are higher than other categories. Specifically, for stratospheric ozone depletion, for which the difference between both cases is 50.7%, in Case a, adhesive use is reported in a cumulative sense as "adhesive, for metal" from the ecoinvent database, while in Case b, three different types of adhesives were identified, and the quantity of actual use was reported, which was more than reported in Case a. More adhesive use leads to increased VOC emissions, which is directly correlated with increased stratospheric ozone depletion [56, 57] shown in Table 5. No direct correlation could be established for the increase

Table 6 Monte carlo simulation results

Case		a				b			
Impact category	Reference unit	Mean	SD	5% percentile	95% percentile	Mean	SD	5% percentile	95% percentile
Fine particulate matter formation	kg $PM_{2.5}$ eq	0.00467799	0.0006365	0.00371652	0.005840327	0.00546124	0.0004835	0.0047691	0.006292212
Fossil resource scarcity	kg oil eq	0.92533113	0.1161182	0.74360395	1.132668861	1.09212234	0.0719276	0.982067302	1.22113625
Freshwater ecotoxicity	kg 1,4-DCB	0.24865601	0.2030532	0.128433959	0.502664819	0.31363286	0.3052836	0.165604283	0.660259225
Freshwater eutrophication	kg P eq	0.00116587	0.0006269	0.000527061	0.002260304	0.00130124	0.0006372	0.000607422	0.002386444
Global warming	kg CO_2 eq	2.45880658	0.3147205	1.983011725	3.00036528	2.94891377	0.2085724	2.646263455	3.301426466
Human carcinogenic toxicity	kg 1,4-DCB	0.37362538	0.5647855	0.133144229	0.964637981	0.43104681	0.5294201	0.17511648	1.012801474
Human non-carcinogenic toxicity	kg 1,4-DCB	8.04593298	18.93957	1.635227178	17.85321113	9.126128	12.258245	1.804666597	23.66870438
Ionizing radiation	kBq Co-60 eq	1.69377161	2.6479111	0.245634596	5.942267365	1.64578025	2.1146502	0.259076148	5.428034671
Land use	m^2a crop eq	0.16512098	0.0348684	0.121470278	0.220357229	0.1745082	0.0400608	0.135164036	0.226934693
Marine ecotoxicity	kg 1,4-DCB	0.34226099	0.2860221	0.175094617	0.70266405	0.43061303	0.4323187	0.223200401	0.924621434
Marine eutrophication	kg N eq	0.0001961	4.108E-05	0.000153702	0.000241181	0.00032777	6.241E-05	0.000291316	0.000368273
Mineral resource scarcity	kg Cu eq	0.11975712	0.0158307	0.096529885	0.147926153	0.12645415	0.0101956	0.111281387	0.144169457
Ozone formation, Human health	kg NO_X eq	0.00597727	0.0007633	0.004843692	0.007336631	0.00717186	0.0005466	0.006424742	0.008091371
Ozone formation, Terrestrial ecosystems	kg NO_X eq	0.00633008	0.0008068	0.005116709	0.007769478	0.00759181	0.0005718	0.006801035	0.008560236
Stratospheric ozone depletion	kg CFC11 eq	6.9746E-07	1.368E-07	5.16085E-07	9.08005E-07	1.5115E-06	1.917E-07	1.31409E-06	1.74769E-06
Terrestrial acidification	kg SO_2 eq	0.00830676	0.0011756	0.006603191	0.0102795	0.00985739	0.0009235	0.008649192	0.011379596
Terrestrial ecotoxicity	kg 1,4-DCB	6.00844663	1.8259157	3.935013519	9.535539034	7.00781316	1.8147933	4.954239451	10.16672173
Water consumption	m^3	– 0.0018882	0.2552274	– 0.430957573	0.403481374	0.01121097	0.3439861	– 0.622756976	0.524618204

in Marine Eutrophication, but more amount of material is used and wasted in making the pair of shoes, as reported in Case b as compared to Case a, and can be the reason for more material leeching into the ocean through soil and water streams [47] but needs further investigation. These significant differences show an advantage in modelling the foreground system in appropriate detail. Table 4, compared with Table 1, shows all the missing pieces of information without using the SMS model. Sometimes, not all consumables are recorded, as we have seen in Case a, due to poor human judgements, but using the SMS model helped record even the smallest amounts of consumables like tissue, varnish, thread, velcro, labels, etc. These small amounts may not be significant in one process or a factory. But, modern products go through multiple manufacturing processes at various factories before reaching the final customers, and such small errors at every stage in data collection can lead to incomplete LCA results portraying an incomplete picture of the environmental impacts associated with the product. Modelling the foreground system in detail provides the basis for a reliable and robust LCA. The results show a difference in impacts, reinforcing the eed for the SMS model. The SMS model has the capability to guide all kinds of data collection from manufacturing systems. Specifically, for LCA, we found the relevance of modeling Material Objects, Equipment, Energy, Time, and waste flows which helped us track raw materials, parts, consumables, wastes, etc., with energy consumption at each station.

7 Future work

Objects, Equipment, Time, and Energy elements of the SMS model were used for collecting inventory data in our study. This data collection was based on LCI requirements. However, there is potential to use all the other elements of the SMS model for obtaining more detailed information about the system and hence a more reliable LCA. Energy consumption was not measured in real time because of the constraints of the factory. There was limited access to the resources, and instrumenting the factory was not allowed. This limitation will be overcome in the future study, using real-time energy data from a different manufacturing plant. Further, based on this model, a Shop Floor based LCA can also be developed for advanced manufacturing systems, which can be used to identify environmental hotspots and develop production plans accordingly. The SMS model can model complex manufacturing systems, but the complexity of storing information increases as the size of the manufacturing system increases. To address that, we will use formal language like XML or a Systems Engineering modelling language to represent our model or create a software tool to incorporate the SMS model.

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Declarations

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

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