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Increasing Resource Efficiency of Manufacturing Systems using a Knowledge-Based System

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Abstract

Nowadays, companies often implement sustainability strategies in order to react to changing market demands and reduce their environmental impacts and resource related costs. In this context, the identification and exploitation of resource saving potentials is a challenging issue. Depending on the knowledge and experience of the persons in charge, promising improvement measures might be found or remain undetected. At this point, knowledge-based systems can come into play, providing expert knowledge to support planners and decision-makers with the identification of specific improvement measures. This work presents such a knowledge-based system, which is able to identify improvement measures on machine and process chain level through rule-based reasoning. In order to exploit these potentials, suitable improvement measures are assigned automatically from a knowledge database. The application is demonstrated with a case from the metal mechanic industry.

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Keywords: Knowledge-Based System, Rule-based Reasoning, Resource Efficiency, Improvement Measures, Decision Support

1. Introduction

Economic activities are strongly related to demands for resources such as materials, energy and water. A growing world population, natural resource depletion and the destruction of eco-systems induce an urgent need for industry to act in a more sustainable manner by reducing their demands for these resources. Motivated by this, manifold methods, tools, models and procedures have been developed in research and applied in practice in order to improve the sustainability of products and processes [1]. For many of these, main challenges are related to the identification of improvement areas, strategies and specific measures. Although many approaches help to identify general areas for improvement like critical life-cycle stages, manufacturing steps or material choices and propose general improvement strategies, they usually fail in naming specific measures. The reason for this cannot be seen in the general availability of knowledge about improvement measures, but rather in a lack of systematic identification procedures, insufficient knowledge management and hardly available experts. The problems can be observed in all types of companies: In small and medium sized enterprises, experts who carry improvement knowledge and could apply methods are often not existent. In large companies, experts may be available, but they are widely distributed while their knowledge is tacit and therefore not directly accessible. In both cases, a systematic support in the step of measure identification could improve the quality of decision making. Further, costs and efforts for identification and evaluation of improvement measures could be reduced. The approach presented here aims to provide this support by means of a knowledge-based system (KBS), giving concrete advice on how to achieve actual improvements. The system is intended to identify improvement measures, which address the process perspective of manufacturing systems by using rule-based reasoning.

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2. Background

2.1. Improvement strategies and measures to increase resource efficiency in manufacturing

Several sources provide general strategies and specific measures for improving the resource efficiency and hence the economic and environmental sustainability of manufacturing. While general improvement strategies usually are constituted by a broad applicability to different systems, specific measures are concretely targeting at individual objects. Various examples for both can be found in academic literature, sustainability reports, corporate websites, good practice repositories, organizational or governmental websites and reports. A broad overview addressing typical improvement strategies at all manufacturing system levels from process unit to value chain level is given by Duflou et al [1]. As one popular example for general strategies, the seven types of waste in manufacturing ("muda") according to the lean management philosophy can be mentioned [2]. By avoiding or reducing transportation, inventory, motion, waiting, over-processing, over-production and defects, significant resource savings can be reached. However, the approach targets at "lean" manufacturing, which does not necessarily correspond with "green" i.e. environmental targets [3]. Another established example for general strategies was introduced by Sarkis and Rasheed as "three Rs strategy" [4, 5]. They propose to apply the strategies reduce, remanufacture and recycle & reuse to improve the environmental impacts of manufacturing. Rashid et al. compared the four sustainable manufacturing strategies waste minimization, material efficiency, resource efficiency and eco-efficiency as the most popular strategies described in theory and practice [6]. They concluded that all strategies contribute to a sustainable development with no strategy being superior. In the context of energy value stream management as lean management method, Erlach & Westkämper have introduced eight general design principles in order to increase energy efficiency of manufacturing processes [7]. They address both technical aspects (e.g. use best available technology, reuse of energy) but also organisational aspects (e.g. energy oriented order sequence, levelling of energy demand peaks). In contrast to these general strategies, specific measures focus on specific processes like casting or machining, on machine components like engines or pumps or on functions such as heat or waste recovery. Despeisse has collected and classified about 1000 specific sustainable manufacturing measures from sources described and sorted them according to the underlying strategies [8]. Apart from public measure sources, confidential databases exist within organisation. As an example, the Volkswagen AG established a worldwide database for improvement measures. Beneath others, it covers about 12.000 measures aiming only at energy efficiency [9].

2.2. Identification procedures for improvement measures

As described ahead, a general lack of improvement strategies and measures enhancing resource efficiency in manufacturing cannot be stated. Instead, the main challenge in practice is the identification of suitable and promising measures for a system under assessment. Here, procedures are needed in order to filter relevant measures and sort them according to their potential or applicability. Many procedures found in literature base on general improvement strategies as described in section 2.1, which are ranked according to a proposed application sequence. Popular examples are the hierarchy of waste management, which has first been introduced in the Waste Framework Directive (75/442/EEC) of the European Commission [10, 11]. It provides a clear prioritization of strategies for waste management, ranging from prevention (highest priority) to final disposal (lowest priority). In analogy to the waste hierarchy, an energy hierarchy has been proposed by Wolfe and extended by other authors and institutions [12, 13]. It puts highest priority on demand reduction by avoiding energy wastage, followed by demand reduction through energy efficiency measures. The last sustainable and therefore preferable option is to exploit fossil fuels by using conventional energies. Based on both waste and energy hierarchy, Despeisse derived a general improvement hierarchy for sustainable manufacturing [8]. It follows the steps prevention, waste reduction, resource reduction, reuse waste as resource and substitution. However, the hierarchy is intended to be used in an iterative and flexible manner, as the best strategy to follow depends on the object to improve. Figure 1 summarizes the described hierarchies for waste, energy and sustainable manufacturing.

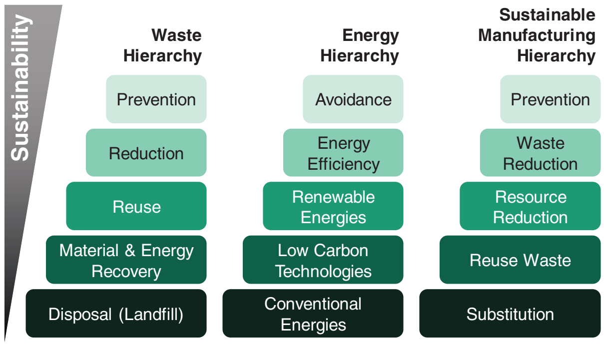


Figure 1: Improvement hierarchies for waste, energy and sustainable manufacturing [8, 10 - 13]

All these procedures can lay the foundations for an improvement of resource efficiency in manufacturing. Nevertheless, they do rarely provide specific measures, which are suitable to the current situation and directly applicable. Consequently, experts are needed to apply the strategies on the specific systems under assessment, deriving and rating specific measures. Apparently, the result is highly depending on the knowledge and experience provided by the experts. One approach to overcome these shortcomings is the application of benchmarking the current system against systems reflecting best available technology or applying best practice. By comparing both the performances and setups, conclusions about promising improvement measures can be drawn. Dehning describes this procedure of knowledge transfer based on a corporate knowledge database from the industrial perspective [9]. Still, this procedure is limited to an application within large companies, as it bases upon an internal best practice database. In addition, expert knowledge is needed to compare the manufacturing system configuration (processes, machines, resources used) and judge about the transferability of measures.

As another alternative to identify measures, matching and data retrieval approaches using knowledge databases can be mentioned. Several corresponding approaches have been described, while most of them address the product perspective. For instance, Herrmann developed a knowledge-based system using fuzzy logics in order to support product developers in designing recyclable products [14]. In addition, commercial software tools like the CES Selector© support product developers by providing material specific knowledge in the design phase [15]. Addressing the process perspective, Schmid developed a knowledge-based analysis tool for a first rough estimation of energy improvement potentials [16]. It focuses on measures for compressed air, cooling and heating systems. However, the approach rather aims at assessing the impact of improvement measures than to identify them. Weinert et al. presented a framework for lean and green manufacturing, providing a structured procedure to identify improvement areas and appropriate improvement measures [3]. A guideline book contains extensive information for each measure such as prerequisites, related efforts and practical examples. Drawbacks can be seen in the significant efforts for manual measure selection. Fischer developed a solution finding process (SFP) to prioritize "lean and green" improvement measures [17]. Therefore, the measures are described in a formal way and matched with the results coming from an extended value stream analysis of the factory. Extensive information is needed to characterize each measure, hampering industrial applicability. Another approach is presented by Bergmann, who developed a concept to evaluate the influence of design elements such as lean management tools on functional requirements of a production system based on axiomatic design [18]. Still, the application requires well-grounded expert knowledge and the derived measures are not specific enough to be directly implementable.

To sum up the focuses of existing work, a lack of procedures to identify specific improvement measures for industrial application can be stated. The provision and matching of knowledge by means of a KBS is regarded as promising solution, hence their typical elements and functionalities are explained in the following.

2.3. Knowledge-based systems and rule-based reasoning

Knowledge-based systems are able to help decision-makers in a decision situation by providing documented knowledge. Their application is widely spread over different sectors, ranging from resource extraction over production, business management or medicine. Typical use scenarios are related to data interpretation, surveillance, diagnosis, planning, design as well as prognosis. Figure 2 displays the typical structure of a KBS [19]. The main characteristic of a KBS is the separation of knowledge storage within a knowledge database and knowledge processing performed by an inference machine [19]. The knowledge database serves as data backbone of the system. It can contain knowledge from the analysis of specific use cases on the one hand and general domain specific knowledge on the other hand [19]. A distinction is made between declarative knowledge (like improvement measures) and procedural knowledge (like application rules) [20]. The latter are usually defined as "IF… THEN…" conditions. The inference component is the problem-solving component of the system, applying the rules to find a solution for a specific problem [19]. Problem related data or information is fed into the system through an interview component as part of a user interface, which does also display the results. The user interface may contain additional components such as an explanation component as well as a knowledge acquisition component, allowing to add, change or remove knowledge from or to the knowledge database [19].

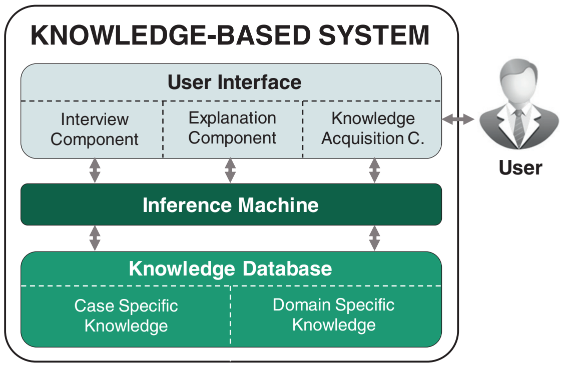


Figure 2: Structure and elements of a KBS, adapted from [19]

3. Concept

The concept described subsequently follows the idea that KBS can help to identify improvement measures systematically and efficiently by providing expert knowledge. Hence, a concept for a KBS has been developed and implemented as prototype in Microsoft Excel©. From the beginning, a seamless integration with the decision-making toolbox described by Blume et al. has been aspired [21]. So far, the main functionality of the toolbox was to assess the current resource efficiency of factories and value chains. Hence, it was built upon material and energy flow models of the value chains, applying methods such as combined energy value stream mapping, material flow simulation and life cycle assessment. As results, technical, economic and environmental key performance indicators (KPI) were obtained on different system levels (e.g. indicating utilization rates per machine, quality related material losses within a factory or total costs per product along the entire value chain). Apart from assessing the status quo, the toolbox was already able to identify potential areas of improvement by detecting critical processes and parameters through method application and sensitivity analyses. This could for instance be the electrical energy input and quality rate (critical parameters) of a hardening process (critical process). Improvement measures could be tested virtually before implementing them in the real world value chains. However, the toolbox was not designed to identify specific improvement measures so far. Instead, the identification was carried out rather manually. By extending the toolbox with a KBS, this gap could be closed now (see Figure 3). For this reason, critical processes and parameters as well as supplementary data such as product, process and production parameters are transferred from the toolbox to the KBS through a newly developed interface. An identification and ranking of suitable improvement measures is then carried out automatically by the KBS. The structure of the KBS is oriented to the general structure of KBS introduced in section 2.3. Hence, a knowledge database has been implemented, containing improvement measures ("measure database") and matching rules ("rule database"). Through a (user) interface, the toolbox data is imported into the KBS. The matching engine corresponds to the inference component, applying rules in order to match measures to the critical processes and parameters.

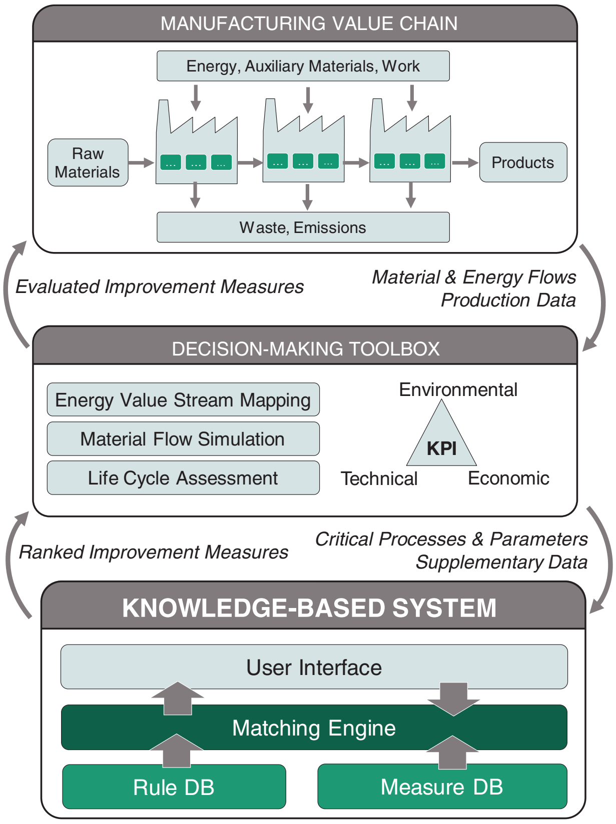
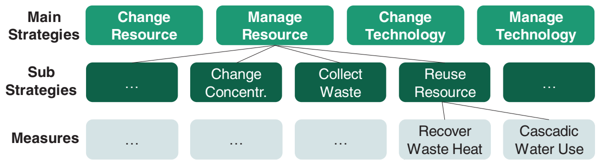


Figure 3: Concept of the KBS and integration with the existing decision-making toolbox

The functioning of the different KBS elements is briefly explained in the following. The **measure database** contains improvement measures addressing industrial manufacturing processes. The database has been created using case and domain specific measures found in literature as well as individual knowledge acquired in industrial and research projects. The measures were structured hierarchically (see Figure 4), distinguishing main strategies, sub strategies and measures. The specificity increases from top to bottom level, while the broadness of applicability decreases. The main strategies and sub strategies have been adapted from Despeisse [8]. In order to assess their applicability for a specific case, each measure has been described individually using few criteria, indicating for which processes it is applicable, at which system parameter category it mainly targets and which additional constraints need to be fulfilled for implementation. Concerning the process, both a general process category (e.g. separating) and a specific process type (e.g. grinding) are distinguished according to DIN 8580 [22]. The distinction is done due to a potential transferability of measures within the same process category, e.g. between milling and turning processes. Measures, which can be applied to multiple processes, can be characterized accordingly by selecting several (or all) process categories or types. The parameter category refers to the system parameter, which the measure is mainly aiming it. Six parameter categories are differentiated according to the results provided by the decision-making toolbox: energy input, material input, workforce input, rework rate, quality rate and processing time. Under energy and material input, all kinds of energy and materials are summarized, while the other parameter categories are referring to single values. Measures may target more than one parameter category, e.g. increasing the cutting speed of a milling process may both improve the energy input and the processing time. Figure 4 exemplarily shows some measures to recover waste heat. Obviously, the applicability of these measures is not limited to a specific process type, as they are generally applicable for processes generating waste heat. If recovered heat is taken as input of the same or another process, energy is saved. Thus, the main target parameter category of these measures is the energy input. Depending on the measure, additional constraints might need fulfillment to apply it. For instance, the installation of a heat pump is reasonable for waste heat temperature levels of 150°C or below, while the installation of a steam turbine is meaningful for temperature levels from 400 °C.



Recover waste heat

No.			1	2	3	…
Name			Heat Pump	ORC	Steam Turbine	…
Process Category			All	All	All	…
Process Type			All	All	All	…
Parameter Category			Energy Input	Energy Input	Energy Input	…
Constraints	Process	Temperature [°C]	< 150	> 150	> 400	…
		Utilization [%]	-	-	-	…
	Product	Material	-	-	-	…
		…	…	…	…	…
	Production	Shifts per day	-	-	-	…
		…	…	…	…	…

Figure 4: Structure and description of improvement measures in measure database of the KBS

The rules in the **rule database** evaluate the matching level between measures and the identified improvement areas by comparing parameter category, process category and process type. In addition, eventual constraints of each measure are checked using the supplementary data submitted from the toolbox. Like indicated in Figure 5, five matching levels from 0 to 100 can be reached depending on the criteria fulfillment. If no criteria matches, a matching level of 0 is assigned. The corresponding rule in the rule database can be expressed as: *"IF parameter category matches not AND process category* *matches not AND process type matches not AND constraints matches not THEN assign matching level of 0".* The rules for each other row can be expressed following the same logics. As soon as either parameter category, process category or constraints match, the measure receives a matching of 25, indicating a measure which does not fit well, but might have at least a certain transfer potential. If a measure matches all criteria (matching level 100), it is tailored to the critical process and also fulfills eventual additional constraints. The **matching engine** is liable for applying the rules for all measures of the measure database. As a result, every measure is assigned to a matching level. The measures are then sorted with respect to their matching level in order to receive a prioritized list. Further sortings are not carried out, i.e. a sorting within the same matching level is not performed. Actual improvement potentials as well as invests for measure implementation are not considered at this stage, as they are highly individual and general estimations seemed not to be meaningful. The measure list is finally displayed to the user in the **user interface** and transferred to the decision-making toolbox to allow further quantitative measure assessments.

Improvement Measures

Parameter Category	Process Category	Process Type	Constraints	Matching Level
○	○	○	○	0
●	○	○	○	25
○	●	○	○	
○	○	○	●	
○	●	○	●	50
○	●	●	○	
●	○	○	●	
●	●	○	○	
○	●	●	●	75
●	●	○	●	
●	●	●	○	
●	●	●	●	100

Figure 5: Criteria to assign matching levels for improvement measures

4. Application

In the following, the practical application of the KBS is demonstrated with an industrial case study from the European metal mechanic sector. As described by Blume et al. [21], an energy and material flow model of the whole value chain had been set up in the decision-making toolbox in order to identify improvement areas. This analysis had shown several "hotspots" along the value chain concerning the economic, environmental and technical KPI of interest. One of the most critical parameters is the electrical energy demand of a hardening process, which is carried out using a hardening furnace. Thus, a strong motivation to improve this specific parameter can be expected from the company's perspective. Instead of manually deriving possible measures to reduce the energy input of the hardening process, the evaluation results are transmitted to the KBS, accompanied by supplementary process data such as utilization rate, quality rate and temperature level. This supplementary data is needed to check whether the process fulfils the constraints of certain measures, hence to figure out if they are well applicable. The matching engine of the KBS then checks the matching rules for all entries in the measure database, assigning each measure to a distinct matching level (0, 25, 50, 75 or 100). This procedure is carried out automatically without any action to be taken by the user. He or she receives a ranked measure list as result, starting with the best matching measures and ending with measures, which only match partly. In Figure 6 this procedure is illustrated and an excerpt of the resulting measure list for the use case is presented. Apparently, the KBS has identified several measures receiving a match of 100. According to the matching level definition, these measures are addressing the parameter category "energy input" of a hardening process and the process fulfills their additional constraints. For the case assessed, perfect matching measures are for instance a replacement of electricity as main energy carrier by natural gas (strategy "change resource") or heat recovery using an ORC (strategy "manage resource"). Other exemplary measures like the recovery of heat losses using a heat pump do not get the full rating, as for instance their constraints do not match with the critical process characteristics. However, this does not necessarily mean that they have a lower resource saving potential. After the matching is performed, some of the measures can directly be assessed by means of the toolbox. This applies to the replacement of electrical energy with natural gas, which can be done easily in the decision-making toolbox by changing the input energy carrier for the process. Furthermore, the potential of a machine switch-off in non-productive times can be assessed, e.g. by reducing the electrical load demand of the machines for non-productive states. However, a perfect switch-off in all non productive times is hardly achievable in practice. In order to verify these first impact estimations and to assess more complex measures like heat recovery, expert consultations are still required.

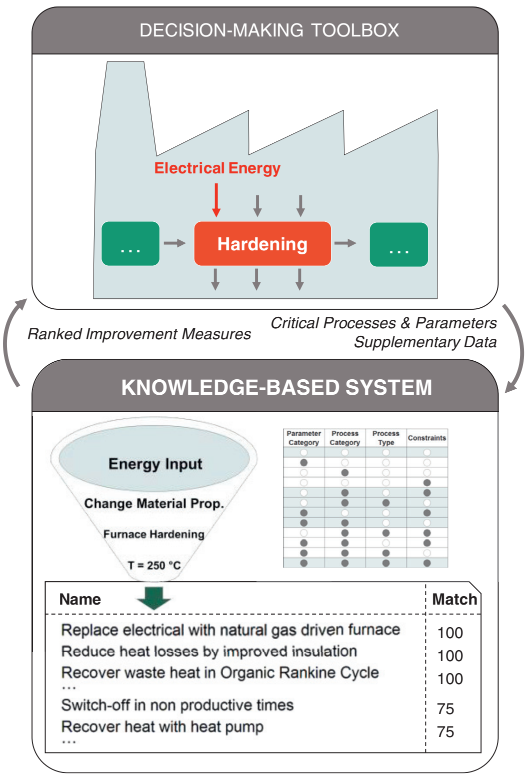


Figure 6: Exemplary application of the KBS

5. Conclusions and Outlook

Motivated by the challenge to systematically identify improvement measures addressing resource efficiency in manufacturing, this paper describes the concept and software implementation of a KBS. It is capable to propose suitable measures for cases analyzed with the existing decision-making toolbox. Therefore, a rule-based matching procedure has been developed in order to select suitable measures according to their characteristics. The implementation in a standard software makes the KBS easy accessible. It can therefore replace or at least support experts in the step of measure identification. Due to the open structure of the knowledge database, both measures and matching rules can be adapted and extended with only slight manual efforts. First testings in real use cases revealed a high potential to simplify the step of systematic measure identification as part of a continuous improvement process regarding resource efficiency. However, the measure ranking provided by the KBS does neither automatically correspond to the potential impact in terms of resource efficiency nor can it reflect important economic indicators such as the payback time. Thus, supplementary expert knowledge is still necessary in order to assess which system parameters will be influenced through measure application and to which extend they might change. One approach towards the automation of this impact quantification could be based on case specific knowledge to extend the measure characterization such as invest, achieved resource savings or payback times. Though, this data is rarely available for many measures, as it is usually not or only partly published by the implementing companies and could therefore not be considered in the KBS so far. In addition, also further frame conditions and assumptions about the manufacturing system would be required in order to realistically estimate the impacts of a measure transfer from one system to another. Consequently, a quantification would go along with significant additional data collection. Another possible extension of the KBS relates to the seamless integration of measures from other sources than the manually filled measure database. The internet could be such a source, as it brings together many different publications from scientific, industrial and governmental domains. Hence, the availability of solutions for very specific questions could be improved. Main challenges can be seen in the automatic detection of these solutions, e.g. by using web search engines and applying data and text mining algorithms to the search results. First attempts in this direction have shown that many search results are not containing sufficient information about specific measures. Further, the measures are not described in a standardized way, preventing an automated matching following the proposed rules. Yet, it would be possible to carry out automatic web searches in the background in order to provide the user with potentially relevant websites or publications.

Acknowledgements

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References

[1] Duflou JR, Sutherland JW, Dornfeld D, Herrmann C, Jeswiet J, Kara S, Hauschild M, Kellens K. Towards energy and resource efficient manufacturing: A processes and systems approach. CIRP Annals-Manufacturing Technology 2012;61(2):587-609.
[2] Ohno T. Toyota Production System. Int J Oper 1988;4:3-11.
[3] Weinert N, Fischer J, Posselt G, Herrrmann C. Lean and green framework for energy efficiency improvements in manufacturing. Proc. 11th Glob. Conf. Sustain. Manuf. Innov. Solut.:461-466.
[4] Sarkis J, Rasheed A. Greening the manufacturing function. Bus. Horiz. 1995;38(5):17-27.
[5] Sarkis J. Manufacturing strategy and environmental consciousness. Technovation 1995;15(2):79-97.
[6] Abdul Rashid S, Evans S, Longhurst P. A comparison of four sustainable manufacturing strategies. Int. J. Sustain. Eng. 2008;1(3):214-229.
[7] Erlach K, Westkämper E. Energiewertstrom: Der Weg zur energieeffizienten Fabrik. Stuttgart: Fraunhofer Verlag; 2009.
[8] Despeisse M. Sustainable Manufacturing Tactics and Improvement Methodology: A structured and systematic Approach to identify Improvement Opportunities. Cranfield University; 2013.
[9] Dehning P. Steigerung der Energieeffizienz von Fabriken der Automobilproduktion. Autouni Schriftenreihe 2017;104.
[10] European Commission. Waste Framework Directive 75/442/EEC. 1975.
[11] Hansen W, Christopher M, Verbuecheln M. EU Waste Policy and Challenges for Regional and Local Authorities. Background Paper for the Seminar on Household Waste Management 'Capacity Building on European Community's Environmental Policy'. Ecologic; 2002.
[12] Wolfe P. A proposed Energy Hierarchy. WolfeWare; 2005.
[13] Institution of Mechanical Engineers. The Energy Hierarchy. Westminster; 2009.
[14] Herrmann C. Unterstützung der Entwicklung recyclinggerechter Produkte. Essen: Vulkan Verlag; 2003.
[15] Grantadesign. CES Selector. 2017. [Online]. Available: https://www.grantadesign.com/products/ces/. [Accessed: 02-Oct-2017]
[16] Schmid C. Energieeffizienz in Unternehmen. ETH Zürich; 2004.
[17] Fischer J. Prioritizing Components for Lean and Green Manufacturing. Essen: Vulkan Verlag; 2017.
[18] Bergmann L. Nachhaltigkeit in Ganzheitlichen Produktionssystemen. Essen: Vulkan Verlag; 2009.
[19] Puppe F. Einführung in Expertensysteme. 2nd ed. Berlin, Heidelberg: Springer; 1991.
[20] Ullmann G. Expertensystem zur Bereitstellung von Produktionssystem-Wissen für den Werkzeug- und Formenbau. PZH; 2010.
[21] Blume S, Kurle D, Herrmann C, Thiede S. Toolbox for Increasing Resource Efficiency in the European Metal Mechanic Sector. Procedia CIRP 2017;61:40-45.
[22] Deutsches Institut für Normung: DIN 8580:2003-09 - Fertigungsverfahren - Begriffe, Einteilung. Berlin: Beuth Verlag; 2003.