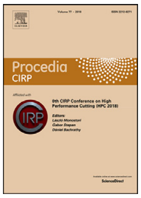
Procedia CIRP 90 (2020) 171–175

Contents lists available at ScienceDirect

Procedia CIRP

journal homepage: www.elsevier.com/locate/procir



Environmental assessment of consequences from predictive maintenance with artificial intelligence techniques: Importance of the system boundary

Annelie Carlson*, Tomohiko Sakao

Division of Environmental Technology and Management, Department of Management and Engineering, Linköping University, SE-581 83 Linköping, Sweden

ARTICLE INFO

Keywords:
Artificial intelligence
Predictive maintenance
System boundary
Life cycle assessment

ABSTRACT

This paper analyses a case of maintenance planning that was researched in previous work and thereby improved using predictive maintenance with an artificial intelligence (AI) technique. In particular, the environmental implications are presented using a life cycle assessment. Using AI to develop maintenance planning could be a feasible method that can outperform other strategies. However, the results of this analysis show that the economic and environmental performance depends largely on the assessment setting. Therefore, applying appropriate system boundaries and functional unit is of major importance to avoid sub-optimization when maintenance planning is developed.

1. Introduction

A vast amount of data from products in the use phase is collected and stored. At the same time, a huge market potential exists for applying artificial intelligence (AI) techniques to the data to improve maintenance services. However, despite the data available and proven AI techniques, the industrial application of these is still in its infancy. By taking advantage of these opportunities, the capacity and competitiveness of industry and the business and environmental performance can be further enhanced.

Maintenance has been vital for manufacturers of complex products from the competitiveness and financial viewpoints for many years (Takata et al., 2004; Roy et al., 2016). Today, maintenance is meeting new opportunities provided by two megatrends in industry. First, industries are experiencing transitions towards Industry 4.0, involving the cyber-physical system (CPS) (Monostori et al., 2016), AI (Russell and Norvig, 2010), and connectivity of a large number of devices in the world (Lee et al., 2013). Second, from the environmental sustainability viewpoint, maintenance is expected to play a crucial role (Umeda et al., 2012) because it can prolong products' lives and is prioritized over material recycling according to the waste hierarchy (reduce-reuse-recycle). Even for the circular economy (Webster, 2015), maintenance is supposed to play a crucial role. These two megatrends are bringing new opportunities to manufacturing industries (e.g., Bumblauskas et al., 2017): maintenance could be lifted to a higher level in terms of accuracy, real-timeliness, cost savings, and resource efficiency (Ren et al., 2018). To further improve the outcome and to avoid sub-optimization, it is also of importance to define and use relevant system boundaries and objectives when applying these opportunities (Abdoli et al., 2019).

Today, many complex product manufacturers who provide maintenance as part of their product/service system (PSS) (Meier et al., 2010) can access a huge amount of data through the Internet of Things (IoT) from products in use that is potentially useful for maintenance. In addition, such data is possible to be collected, transferred, stored, and analyzed with the new technologies. AI techniques are applicable to the data to capture information or knowledge of value. The huge potential for AI techniques is acknowledged by many companies to create new value in maintenance. However, there exists a lack of knowledge to facilitate practitioners in exploiting the AI techniques in maintenance with consideration of environmental and economic consequences.

This paper aims to fill the knowledge gap by showing the environmental consequences of predictive maintenance with AI techniques and discussing their implications. Here, the environmental assessment of a hypothetical case with the maintenance of wind

---

* Corresponding author.
E-mail address: annelie.carlson@liu.se (A. Carlson).

https://doi.org/10.1016/j.procir.2020.01.093

turbines researched in previous work (Holmgren, 2019) is performed, followed by the presentation of a comparative discussion with the environmental assessment of maintenance of products in other sectors using industry data.

The remainder of this paper consists of the following: Section 2 describes the knowledge gap to be addressed by this paper in a more specific manner. Next, Section 3 presents the materials and method adopted by this paper. Sections 4 and 5 then show and discuss the results, respectively. Finally, Section 6 concludes this paper with future work.

2. Knowledge gap and research motivation

In research and development for maintenance, much effort has been given to research about data collection including sensors, while research about how to utilize the collected data to create or improve services is both missing and demanded. A large and increasing number of articles have been published in, e.g., the journal Sensors; however, the articles concerning value creation from data are much fewer. More precisely, a comprehensive literature review (Wamba et al., 2015) found only 62 out of 1153 articles about value creation of big data-related topics that were deemed relevant for value creation, and concluded that "very few studies have been conducted to assess the real potential and value of data". Clearly, techniques that are needed to enhance maintenance to a higher level exist, but from the scientific perspective, assessment and evaluation of the techniques' implications are among the major missing insights.

These missing insights can be reflected upon considering several layers in a hierarchy for value co-creation, as depicted by Fig. 1: for business enterprises to co-create value with their partners, relevant data needs to be collected from different lifecycle phases such as the use phase (the lowest layer), and data and information need to be managed in computer systems. These are insufficient to co-create value, and the engineering and management process that involves organizational issues needs to be implemented appropriately in companies. It is pointed out that traditional engineering companies will have to adapt their engineering processes and organization also on the context of smart products and services (Tomiyama et al., 2019). Furthermore, this layer is essential because many manufacturers expect Industry 4.0 to enable new business models, such as pay per availability (Lichtblau et al., 2015). Note that this hierarchy is not unique to maintenance, and a similar one is used for CPS in a more general manner (VDI/VDE, 2013). It should be mentioned that the process of value co-creation using these new technologies (the highest layer) is also significant, as acknowledged in, e.g., Lanza et al. (2019), but beyond the scope of this paper. This gap motivated this paper with a focus on the two layers, including the interactions between them, as depicted by Fig. 1.

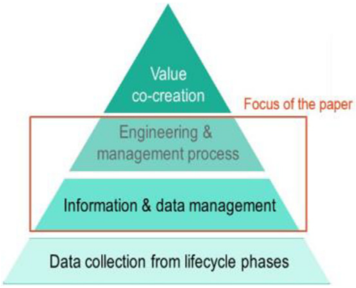


Fig. 1. Focus of the paper in a hierarchy for value co-creation.

3. Materials and method

3.1. Description of the case

The environmental assessment of applying an AI technique in a maintenance strategy is performed for the hypothetical case of an onshore 2 MW wind power turbine. It is a suitable case since reliability and availability are of great importance. Infrequent replacement of major components, in combination with frequent failures of other components, can lead to high operation and maintenance costs and downtime of several weeks with a loss of revenue (Sheng and O'Connor, 2017). A gearbox is addressed as a single component, and its maintenance is evaluated. This is a critical component that can constitute about 20% of the total downtime (McMillan and Ault, 2008, Hau, 2013). The cost associated with reactive maintenance of a gearbox is also high, where failures can be about 15–20% of the price of the turbine itself (Emanuelsson, 2011). This makes gearbox maintenance a high priority.

3.2. Materials

The maintenance strategies that are used in the environmental analysis (presented in Section 4) were developed and computer-simulated in the work of Holmgren (2019). The three maintenance strategies are general maintenance planning, oracle maintenance planning, and periodic maintenance planning.

General maintenance planning is a strategy where an AI technique is implemented. It is based on an adaptation of the Monte Carlo tree search (MCTS) method and deep reinforcement learning (MCTS-DNN) (Holmgren, 2019), where the modification makes it possible to deal with maintenance planning for stochastic problems. MCTS is a heuristic tree search algorithm that is considered to be a promising method for planning. It differs from most reinforcement learning (RL) methods in that it relies on an external model to solve the modeling problem. The deep reinforcement learning applied uses a deep neural network (DNN) instead of traditional RL, which improves generalization and scalability. Before the simulation, the DNN is trained using a self-play algorithm. The MCTS-DNN generates a search tree using an exploratory action-selection policy and observes the outcome using a simulation model. In this case, the choice of the action with the highest expected outcome in each of the time steps is based on a planning horizon of 9 years and 10,000 iterations.

Oracle maintenance planning is an approach that can preview exactly when a component will fail, and a preventive maintenance action is scheduled the time step before the time of failure. It represents a lower bound of maintenance costs and has no basis in real-world application.

Periodic maintenance planning consists of periodically scheduled maintenance events. Some corrective maintenance will still be necessary since components might fail before the scheduled maintenance due to stochastic failure. An aggressive approach is adopted, which means a higher willingness to accept the risk of a breakdown, and hence the maintenance intervals will be longer.

One hundred independent simulations were performed for each maintenance strategy, and each simulation covers a use phase of 25 years with a decision point each year for what action to choose. For each strategy, there are three actions that can be chosen at every decision point: pass (i.e., do nothing), preventive maintenance (PM), or corrective maintenance (CM). The simulations also include a failure probability, i.e., a description of the degradation over time for a component and the mean time to failure (MTTF). The data necessary for the simulations were built on Ref. Ding and Tian (2012), and the objective was to minimize the overall maintenance cost. The cost elements included were a variable preventive replacement cost, a fixed preventive maintenance cost, a failure re-

Table 1
Bill of material for a 2 MW gearbox and transports.

Material	Amount	Production process
Cast iron	7325 kg	Casting
Steel, low alloy	7325 kg	Forging, rolling
Lubricant oil	315 l	
Transports	Amount	Transport mode
Service technicians	450 km	LDV and passenger car
Oil change device	450 km	Truck 3.5–7.5 ton
Crane base	450 km	Truck 3.5–7.5 ton
Crane	450 km	Truck 7.5–16 ton
Gearbox	450 km	Truck 7.5–16 ton

placement cost, an access cost, and a fixed cost (Ding and Tian, 2012).

3.3. Method

The environmental assessment is based on the life cycle assessment (LCA) method, according to ISO 14040 (ISO, 2006) and ISO 14044 (ISO, 2006). The SimaPro 8.0 LCA software and the EcoInvent 3.0 database are used for the inventory and to define flows of material and emissions throughout the lifecycle (Weidema et al., 2013). The environmental assessment includes the impact category global warming (climate change) measured in kg CO_2eq, and the assessment method used is IPCC 2013 GWP 100a. The functional unit is 1 MWh produced electricity, and the system boundary is the maintenance activities and the material use including extraction, manufacturing, use and end-of-life, and transports needed during a time period of 25 years.

4. Result of the environmental assessment

4.1. Life cycle inventory

The different maintenance events are defined according to the following:

- Pass: Transport of service technician to the wind power site.
- PM: Oil change, incineration of used oil, transport of service technicians, and oil change device.
- CM: Replacement of gearbox and oil, recycling of metal (90%), landfill of metal (10%), and incineration of used oil. Transportation includes transport of the new and the replaced gearbox, of a crane used to change the gearbox and transport of service technicians.

The material content of the gearbox (Elsam, 2004) and the transports are described in Table 1. The assumed transport distances are to and from the site of the wind turbine.

During maintenance, the wind turbine is at a standstill, and in some circumstances, there is downtime in production and hence loss of revenue. In the environmental assessment, the following assumptions are made. Routine maintenance takes place when the wind conditions are favorable, i.e., when the wind speed is too low for the turbine to produce electricity. Therefore, the downtime for a pass event is set to 0 h. For PM, the downtime is set to 8 h based on that an oil change device operated from the ground can change oil in two gearboxes during one working day. CM leads to a downtime of 9 days, including the time needed for planning and performing the replacement, and with the assumption that the replacement gearbox is readily available.

The effect on the loss of electricity production is estimated using the downtime and the average annual production of the wind turbine, which is 25% of the installed capacity (IVA, 2016). The average loss of production due to maintenance events is then estimated to 4 MWh per PM event and 108 MWh per CM event.

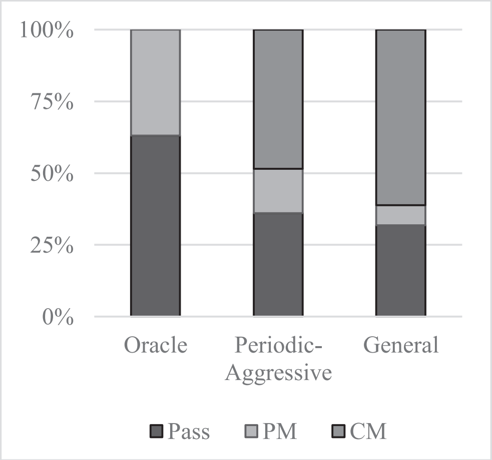


Fig. 2. Relative global warming impact of the different maintenance events.

4.2. Life cycle assessment

Three maintenance strategies that were developed and computer-simulated in previous work (Holmgren, 2019) are compared in this research: oracle, periodic-aggressive, and general. The representative case used for the assessment is the mean value of the number of events, based on the 100 simulations of the respective strategy (Holmgren, 2019). The oracle maintenance planner resulted in 20 pass events and 5 PM events. There were no CM events since the Oracle maintenance planner can foresee break downs and will perform preventive maintenance beforehand. The periodic maintenance planner led to 20 pass, 4 PM, and 1 CM events. With the general strategy, the mean number of events was 21 pass, 2 PM, and 2 CM.

CM led to the highest environmental impact, which is mainly due to the material used in the replaced gearbox. The recycling of material has a positive effect, but the environmental impact of replacing the entire gearbox is still almost eight times as high as the PM event. The effect of this can be seen in Fig. 2, where the relative share of the global warming impact of the three optional maintenance events for the different strategies is presented. Even though there is only one CM for the periodic-aggressive strategy the relative share of the environmental impact is approximately 48%. For the general strategy, with two CM events, the share amounts to around 60% of the total emission of kg CO_2eq/MWh.

Fig. 3 shows a comparison of the global warming impact resulting from the three strategies and for the time period of 25 years. It is also clearly visible in this figure that the general strategy will lead to substantially higher global warming impact compared to the other two options, approximately 100% as much as oracle and 20% higher than periodic-aggressive. This can be compared to the effect on maintenance cost, which shows that the general strategy will lead to a lower total maintenance cost, with around 10%, compared to periodic-aggressive, as presented in Holmgren (2019). This implies that using MCTS with deep reinforcement learning for optimization is a feasible method that could outperform the other strategies. However, in this case, minimizing cost and environmental impact are conflicting objectives, and the reduction in maintenance cost comes with the cost of a higher environmental impact.

5. Discussion

5.1. Relevance of the case to industrial practice

Using the approach of MCTS with deep neural learning can be a relevant method to explore the development of a general main-

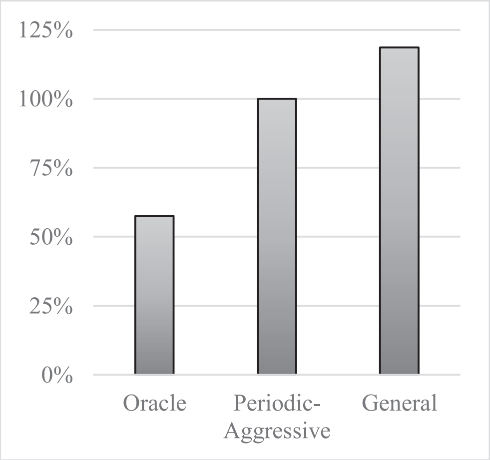


Fig. 3. Relative comparison of the global warming impact of different maintenance strategies.

tenance planner. However, the example that was assessed environmentally in this paper also highlights the importance of using relevant data of high quality in the training for the AI technique if it is to be used for real maintenance planning. The example used has only one PM event for the gearbox, when it, in reality, is several, such as oil change, replace bearings and shafts, etc. The function used could, however, be developed to include several maintenance activities, which would improve the usefulness and the economic and environmental assessment. Furthermore, the model also needs to have a better description of the real-life conditions of wind power. For instance, the designed lifetime of a gearbox is 20 years, but they seldom manage to pass 10 years before some component breaks (Anonymous, 2019). Moreover, according to service technicians, the gearbox of a wind turbine can be changed approximately 3 times over a 20-year period (Emanuelsson, 2011). Hence, the failure probability is also a main parameter and should be based on real data, e.g., from conditioning monitoring. This is data that are collected today, and there are also several models targeting degradation and failure for wind turbines (Seyr and Musulus, 2019); hence, the potential for improvements is within reach.

5.2. Discussion of the system boundary with cases from other sectors

Section 4 describes the environmental impact of maintenance activities using an AI algorithm. The assessment is performed for a hypothetical case, which was simulated in the work of Holmgren (2019). Using deep learning to develop a maintenance strategy, and with the objective to minimize the maintenance cost, also led to lower total cost compared to a strategy with periodic maintenance (ibid.). However, the previous section showed this strategy, with the assumptions made, led to a higher environmental impact compared to the other strategies (see Fig. 3). This implicates that the objective of applying an AI technique can have a considerable effect on the outcome of the environmental performance of the system. Also, the system boundary is of great importance when deciding upon the objective for the maintenance strategies and the evaluation of the effects.

The system boundary of the case and environmental assessment in this paper can be viewed as a traditional business case of a company that sells physical products. Hence, minimizing the cost or increasing the profit of the company selling the products is the focus and one to which the chosen maintenance strategy will contribute. This can, as shown, lead to a situation where reducing the cost is prioritized before resource efficiency and environmental impact. If one instead adopts a system boundary that includes both the provider of a product/service and the customer, which is often relevant in PSS contracts, the focus will most likely be different. In this case, decreasing downtime at the customer could be of main concern, and the maintenance strategies should, therefore, be adapted to lower the risk of a breakdown. Then, a critical component may be replaced as a preventive measure before approaching the end of its' technical life to ensure that the product will still be able to fulfill its function at the user. This will, however, shorten the time the component is used, and the potential of useful life length is not realized. As a result, more components will likely be replaced during a certain time period compared to a periodic maintenance strategy. For the provider of the product/service, this could lead to both higher maintenance costs and higher environmental impact, as was explored with forklift trucks by Birch Tyrberg and Orö (2019). The magnitude of this increase will depend on the specific conditions and the possibilities to make an accurate prediction of breakdowns (Birch Tyrberg and Orö, 2019). However, the overall effect of a PSS will also be dependent on the effect on the customer side. If a reduced downtime of a product means there is less need for redundancy of the products in the system, the system effect could be both reduced cost and better resource efficiency. This is often the case with forklift trucks that are provided as a fleet to a user. As more users demand product availability, providing a fleet becomes more relevant. This also concerns the need to set up the functional unit appropriately.

Sectors where security and safety are of main concern, such as aircraft, can have even broader system boundaries that include a societal interest since the number of stakeholders is usually large. These types of sectors tend to be heavily regulated, and maintenance is viewed as highly prioritized to ensure compliance with the safety protocols. Due to the high safety margins and the way they have been practiced, there can be a significant opportunity to apply AI techniques and develop maintenance strategies where the service intervals and/or the used time of the components are prolonged without imposing on safety levels, i.e., the number of breakdowns do not increase. Such a maintenance strategy will likely have a positive effect on both environmental and cost performance.

6. Conclusions and future work

This paper performed an environmental assessment of given maintenance strategies, one of which is based on an AI technique. It showed that there could be conflicting objectives between reducing cost and reducing environmental impact. The analysis presented in discussion with the cases from other sectors shows that important reasons are the objective used and the system boundaries applied. Furthermore, a product consists of several components, and there can be a variety of maintenance plans for one product. Hence, it is a system of systems (Abdoli et al., 2019). When developing maintenance strategies by, for instance, using AI algorithms, it is important that this is not an isolated activity for one smaller part of a product. Changes in one area will most likely affect other areas, and it should instead be seen as a part integrated into a larger system, and the implementation of new maintenance plans should be evaluated for the overall system. More research needs to be carried out with respect to this in order to investigate impacts on the real world.

It is vital to apply the systems perspective and use relevant objectives and appropriate system boundaries when evaluating the effects of a change in maintenance services. Further research will encompass this, including analyzing the differences between using different objectives and different system boundaries of the same system.

CRediT authorship contribution statement

Annelie Carlson: Formal analysis, Investigation, Writing - original draft, Writing - review & editing. **Tomohiko Sakao:** Conceptualization, Writing - original draft, Writing - review & editing, Supervision.

Acknowledgments

This research is supported by the Simon (New Application of AI for Services in Maintenance towards a Circular Economy) project (No. 2017-01649) funded by VINNOVA, Sweden's Innovation Agency.

References

Abdoli, S., Kara, S., Hauschild, M., 2019. System interaction, system of systems, and environmental impact of products. CIRP Ann. Manuf. Technol. 68 (1), 17–20.

Anonymous. 2019-10-01]; Available from: https://www.windpowerengineering.com.

Birch Tyrberg, M., Orö, P., 2019. Application of AI-based Maintenance: The Economic and Environmental Impact and its Effect on Integrated Product Service Offerings. Linköping University.

Bumblauskas, D., Gemmill, D., Igou, A., Anzengruber, J., 2017. Smart maintenance decision support systems (SMDSS) based on corporate big data analytics. Exp. Syst. Appl. 90, 303–317.

Ding, F., Tian, Z., 2012. Opportunistic maintenance for wind farms considering multi-level imperfect maintenance thresholds. Renew. Energy 45, 175–182.

Elsam, 2004. Life Cycle Assessment of Offshore and Onshore Sited Wind Farms. Elsam Engineering A/S.

Emanuelsson, H.-E., 2011. Basic Maintenance Techniques for Wind Energy Technicians. Heetech Consulting AB, POWER Cluster.

Fosso Wamba, S., Akter, S., Edwards, A., Chopin, G., Gnanzou, D., 2015. How 'big data' can make big impact: Findings from a systematic review and a longitudinal case study. Int. J. Prod. Econ. 165, 234–246.

Hau, E., 2013. Wind Turbines Fundamentals, Technologies, Application, Economics, Third, translated edition Springer-Verlag.

Holmgren, V., 2019. General-Purpose Maintenance Planning Using Deep Reinforcement Learning and Monte Carlo Tree Search. Linköping University Unpublished manuscript, LIU-IDA/LITH-EX-A-2019/001-SE, Department of Computer and Information Science.

ISO, 2006. ISO 14044 – Environmental Management – Requirements and Guidelines. International Organization for Standardization, Geneva.

ISO, 2006. ISO 14040 – Environmental Management – Life Cycle Assessment – Principles and Framework. International Organization for Standardization, Geneva.

IVA, 2016. Electricity Production in Sweden – IVA's Electricity Crossroads Project. Royal Swedish Academy of Engineering Sciences.

Lanza, G., Ferdows, K., Kara, S., Mourtzis, D., Schuh, G., Vancza, J., Wang, L., Wiendahl, H.-P., 2019. Global production networks: design and operation. CIRP Ann. Manuf. Technol. 68 (2), 823–841.

Lee, J., Lapira, E., Bagheri, B., Kao, H.-A., 2013. Recent advances and trends in predictive manufacturing systems in big data environment. Manuf. Lett. 1 (1), 38–41.

Lichtblau, K., Stich, V., Bertenrath, R., Blum, M., Bleider, M., Millack, A., Schmitt, K., Schmitz, E., Schröter, M., 2015. Studie Industrie 4.0-Readiness. VDMA, RWTH, Köln.

McMillan, D., Ault, G., 2008. Condition monitoring benefit for onshore wind turbines: sensitivity to operational parameters. IET Renew. Power Gen. 2 (1), 60–72.

Meier, H., Roy, R., Seliger, G., 2010. Industrial product-service systems – IPS^2. CIRP Ann. Manuf. Technol. 59 (2), 607–627.

Monostori, L., Kadar, B., Bauernhansl, T., Kondoh, S., Kumara, S., Reinhart, G., Sauer, O., Schuh, G., Sihn, W., Ueda, K., 2016. Cyber-physical systems in manufacturing. CIRP Ann. Manuf. Technol. 65 (2), 621–641.

Ren, S., Zhang, Y., Liu, Y., Sakao, T., Huisingh, D., Almeida, C.M.V.B., 2018. A comprehensive review of big data analytics throughout product lifecycle to support sustainable smart manufacturing: a framework, challenges and future research directions. J. Clean. Prod. 210, 1343–1365.

Roy, R., Stark, R., Tracht, K., Takata, S., Mori, M., 2016. Continuous maintenance and the future – foundations and technological challenges. CIRP Ann. Manuf. Technol. 65 (2), 667–688.

Russell, S., Norvig, P., 2010. Artificial Intelligence: A Modern Approach, 3rd ed. Prentice Hall.

Seyr, H., Musulus, M., 2019. Decision support models for operations and maintenance for offshorewind farms: a review. Appl. Sci. 9 (2).

Sheng, S., O'Connor, R., 2017. Reliability of wind turbines. In: Letcher, T.M. (Ed.), Wind Energy Engineering – A Handbook for Onshore and Offshore Wind Turbines. Academic Press, London.

Takata, S., Kimura, F., Houten, F.J.A.M.v., Westkämper, E., Shpitalni, M., Ceglarek, D., Lee, J., 2004. Maintenance: changing role in life cycle management. Ann. CIRP 53 (2), 643–655.

Tomiyama, T., Lutters, E., Stark, R., Abramovici, M., 2019. Development capabilities for smart products. CIRP Ann. Manuf. Technol. 68 (2), 727–750.

Umeda, Y., Takata, S., Kimura, F., Tomiyama, T., Sutherland, J.W., Kara, S., Herrmann, C., Duflou, J.R., 2012. Toward integrated product and process life cycle planning – an environmental perspective. CIRP Ann. Manuf. Technol. 61 (2), 681–702.

VDI/VDE, 2013. Cyber-Physical Systems: Chancen und Nutzen aus Sicht der Automation. Gesellschaft Mess und Automatisierungstechnik (GMA). Thesen und Handlungsfelder.

Webster, K., 2015. The Circular Economy: a Wealth of Flows. Ellen MacArthur Foundation, Isle of Wight.

Weidema, B.P., Bauer, C., Hischier, R., Mutel, C., Nemecek, T., Reinhard, J., Vadenbo, C.O., Wernet, G., 2013. Overview and Methodology – Data Quality Guideline for the Ecoinvent Database Version 3. Swiss Centre of life Cycle Inventories, St. Gallen Ecoinvent Report No. 1(v3).