Journal of Cleaner Production 210 (2019) 1343–1365

Contents lists available at ScienceDirect

Journal of Cleaner Production

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

A comprehensive review of big data analytics throughout product lifecycle to support sustainable smart manufacturing: A framework, challenges and future research directions

Shan Ren [a], Yingfeng Zhang [a, b, *], Yang Liu [c, d, **], Tomohiko Sakao [c], Donald Huisingh [e], Cecilia M.V.B. Almeida [f]

[a] Key Laboratory of Contemporary Design and Integrated Manufacturing Technology, Ministry of Education, Northwestern Polytechnical University, Shaanxi, 710072, PR China
[b] Research & Development Institute in Shenzhen, Northwestern Polytechnical University, PR China
[c] Department of Management and Engineering, Linköping University, SE-581 83, Linköping, Sweden
[d] Department of Production, University of Vaasa, 65200, Vaasa, Finland
[e] Institute for a Secure and Sustainable Environment, University of Tennessee, Knoxville, TN, USA
[f] Paulista University, São Paulo, Brazil

ARTICLE INFO

Article history:
Received 18 July 2018
Received in revised form
31 October 2018
Accepted 3 November 2018
Available online 8 November 2018

Keywords:
Big data analytics
Smart manufacturing
Servitization
Sustainable production
Conceptual framework
Product lifecycle

ABSTRACT

Smart manufacturing has received increased attention from academia and industry in recent years, as it provides competitive advantage for manufacturing companies making industry more efficient and sustainable. As one of the most important technologies for smart manufacturing, big data analytics can uncover hidden knowledge and other useful information like relations between lifecycle decisions and process parameters helping industrial leaders to make more-informed business decisions in complex management environments. However, according to the literature, big data analytics and smart manufacturing were individually researched in academia and industry. To provide theoretical foundations for the research community to further develop scientific insights in applying big data analytics to smart manufacturing, it is necessary to summarize the existing research progress and weakness. In this paper, through combining the key technologies of smart manufacturing and the idea of ubiquitous servitization in the whole lifecycle, the term of sustainable smart manufacturing was coined. A comprehensive overview of big data in smart manufacturing was conducted, and a conceptual framework was proposed from the perspective of product lifecycle. The proposed framework allows analyzing potential applications and key advantages, and the discussion of current challenges and future research directions provides valuable insights for academia and industry.

1. Introduction

Sustainable production and consumption is a competitive strategy for manufacturing enterprises as its implementation can help manufacturers to achieve overall development plans, reduce resource use, degradation and pollution along the whole lifecycle (Roy and Singh, 2017). This strategy can promote practices of resource and energy efficiency and reduce future economic and social costs by offering basic services for all stakeholders. Therefore, servitization, as a high-level term for service-oriented strategies, is gaining attention from many manufacturers. As a result, integration of services and products into one PSS (Gao et al., 2011) to implement sustainable production and consumption strategies has become a popular focus for researchers engaged with sustainability (Tukker, 2015).

Within this context, it has become increasingly important for manufacturers to transform their business models to effectively collaborate with business partners improving their SCA (ElMaraghy and ElMaraghy, 2014; Liu, 2013; Liu and Liang, 2015; Tao et al.,

* Corresponding author. Key Laboratory of Contemporary Design and Integrated Manufacturing Technology, Ministry of Education, Northwestern Polytechnical University, Shaanxi, 710072, PR China.
** Corresponding author. Department of Management and Engineering, Linköping University, SE-581 83, Linköping. Sweden.
E-mail addresses: zhangyf@nwpu.edu.cn (Y. Zhang), yang.liu@liu.se (Y. Liu).

https://doi.org/10.1016/j.jclepro.2018.11.025
0959-6526/

2015). This requires the establishment of a collaborative infrastructure to continuously understand and satisfy customer needs and to reduce environmental impacts (Ahn et al., 2017; Song et al., 2018; 2017b), with seamless inter-connections and resource sharing among different manufacturers. Many advanced manufacturing paradigms, such as lean manufacturing (Holweg, 2007), JIT manufacturing (Huson and Nanda, 1995), agile manufacturing (Sanchez and Nagi, 2001), green manufacturing (Rusinko, 2007), and sustainable manufacturing (Jayal et al., 2010) have been proposed ways to achieve these goals, but these approaches lack visibility and interoperability of manufacturing resources and products.

The major challenges are: 1) Lack of dynamic network infrastructure to link physical and virtual objects; 2) Lack of interoperable EISs to ensure effective integration and centralized management of the heterogeneous lifecycle data; 3) Lack of advanced analytics technologies to perform in-depth analyses of lifecycle data and to provide knowledge support for dynamic lifecycle decisions. The development of information technologies, such as IoT (Perera et al., 2015), SOT (Demirkan et al., 2008), CC (Hamdaqa and Tahvildari, 2012), BDA (Frank Ohlhorst, 2013) are providing new opportunities for manufacturers to solve these challenges. In this context, some new concepts and manufacturing paradigms, such as IoMT (Zhang et al., 2015), service-oriented manufacturing (Gao et al., 2011), CMfg (Xu, 2012; Zhang et al., 2017d), SM (Davis et al., 2015), and industrial BDA (Lee et al., 2015a) have been proposed and used by an increasing number of industrial leaders.

The SM is a new, networked and service-oriented manufacturing paradigm, which evolved from, but extends beyond, the traditional manufacturing and service modes, and integrates many advanced technologies such as IoT, industrial internet, CPS (Y. Zhang et al., 2018e), CC, DM, AI, and BDA (Xu et al., 2015; Kang et al., 2016; Mittal et al., 2016). The SM integrates data management with process expertise to enable flexibility in physical processes to interact within dynamic global markets increasing the profitability of manufacturers (Davis et al., 2012; Thoben et al., 2017). In SM, all manufacturing resources, products, processes and services are intelligent, with open and dynamic inter-connectivity and interactions throughout the entire value chain. Therefore, large amounts of data for heterogeneous manufacturing resources and products are produced along the whole lifecycle. The data can be collected and analyzed by manufacturers according to their requirements for effective and dynamic lifecycle decisions, because realization of the goal of SM depends on autonomous and analytics-based decisions (Davis et al., 2012; Y. Zhang et al., 2018a), which in turn relies on the effective analyses of the massive volumes of data gathered from equipment and processes. Therefore, the BDA in SM becomes a critical issue.

In SM environment, manufacturers utilize advanced analytics technologies, such as BDA-based approaches to improve their efficiency and productivity, and to convert data into useful, actionable information (Lee et al., 2013). BDA also brings potential advantages for SM such as knowledge generation, KPI optimization, predication and feedback to product and process design (Nagorny et al., 2017). According to Kusiak (2017), BDA can help manufacturers to interpret the captured data at all stages of the product lifecycle, to improve their processes and products, and to make manufacturing processes smarter. It has been found that BDA can help to solve the problems of load-unbalance and inefficiency during deployment of a SM system D. Li et al. (2017).

By using BDA to derive value from lifecycle big data and to execute the business strategy of servitization during the whole lifecycle, is one of the possible future trends in creating new added-value and enhancing sustainability in a manufacturing enterprise (Opresnik and Taisch, 2015; Tukker, 2015). Industrial leaders need insights on: how to utilize BDA to exploit the real potential and value of lifecycle big data to make the whole lifecycle decision-making smarter; and how to integrate and apply effectively the advanced technologies of SM and BDA to enhance competitiveness and sustainability. Although, BDA and SM have been individually researched in academia and industry, research combining BDA and SM is in its infancy. Lisbon University and Manchester University jointly organized an International Conference on Sustainable Smart Manufacturing (S2 Manufacturing International Conference, 2016), and ASTM international published a journal series named 'Smart and Sustainable Manufacturing Systems' (ASTM International, 2017). Articles related to similar themes were published in Procedia CIRP (Elsevier, 2012) and IFAC-PapersOnLine (Elsevier, 2015). All these efforts aim to apply advanced sensor, information modeling, computing and data analytics technologies (e.g. IoT, CPS, Cloud, AI) to foster transdisciplinary research focusing on how to make manufacturing systems smarter and sustainable. Despite some progress achieved, limitations exist: 1) they did not address 'sustainability' in-depth using either business models or environmental perspectives; 2) they labeled 'Sustainable Smart Manufacturing' or 'Smart and Sustainable Manufacturing' without adequate definitions of these new terms; 3) they claimed to foster transdisciplinary research and innovation, with the objective of making the manufacturing system smarter and sustainable, but smart and sustainable aspects of other lifecycle stages were seldom addressed. In fact, sustainability and SM were addressed separately.

High quality journal papers that investigated SM and sustainability in an integrated manner are rare. Therefore, a comprehensive literature review is required to provide theoretical foundations that can be adopted to further develop scientific insights in this area, and to help industrial leaders and policy makers make more ecologically and economically sound decisions for the short and long-term.

The traditional SM paradigm mainly emphasizes the flexibility of physical processes, with the goal of optimizing the production processes and operations or maintenance processes of MOL, and responds to dynamic market (Davis et al., 2012). However, other lifecycle stages (i.e. design stage and recovery stage) and the sustainability aspect of the whole processes or systems was not taken into account. As a service-oriented business strategy, servitization has been widely used by manufacturers to undergird their competitive advantage (Opresnik and Taisch, 2015), such as reducing production costs and environmental impact and improving resource efficiency. The servitization of modern manufacturing differs greatly from traditional approaches because of rapid developments in information and data analytics technologies that support the creation and delivery of products and services.

This review investigates how manufacturers can exploit the opportunity arising from combining the key technologies of SM with ubiquitous servitization at all stages of product lifecycle for intelligent and sustainable production. The term SSM is used to encompass the processes. SSM is defined as "a new manufacturing paradigm that integrates and applies the latest information and data analytics technologies in operations and decision-making processes of PLM, to transform the traditional modes of production and operation activities of the whole lifecycle from product-driven mode to data and service-driven mode, and to ultimately achieve an intelligent and sustainable production." Such integration requires merging the strategy of servitization with product design, manufacturing, operation and maintenance, remanufacturing, recycling and recovery stages of PLM. The concept, not expressed in clear form in the literature, is crucial to advance knowledge in this area. Implementation of SSM may help manufacturers to achieve a data-driven and service-driven PLM, and enable the ubiquitous connectivity, dynamic synchronization, and collaborative optimization of all lifecycle business processes. The SSM can help business managers to

minimize resources/energy waste and to reduce or eliminate emissions from industrial processing, thereby making progress towards the goals of intelligent, sustainable, cleaner production, while fulfilling the diverse customer needs for the short and longer-term. Therefore, users of SSM have the objective of promoting the creation and delivery of services, reducing resource usage, degradation and pollution, and improving economic and environmental sustainability by utilizing information and data analytics technologies in the management processes of the whole lifecycle to increase the level of intelligence in decision-making. The differences and connections between the traditional SM and the proposed SSM are compared as presented in Fig. 1.

In comparison with the Industry 4.0 (Kagermann et al., 2013; Hermann et al., 2016) and the traditional SM, the SSM highlights servitization, throughout the product value chain by using advanced information, data analytics technologies, and global optimization of the whole PLM to help industrialists to effectively build upon the insights derived from big data usage. It also emphasizes the goal of improving the intelligent level of design, production, maintenance and recovery through the feedback and sharing of lifecycle data among all stakeholders in the supply chain. Finally, the objectives of minimizing resource inputs and energy wastage, as well as prevention or minimization of emissions can be achieved through sustainable and long-lasting product design, intelligent maintenance and repair, and optimized upgrading, reuse, remanufacturing and recycling.

A large variety of technologies are included in SM or SSM, and due to the significant role for BDA to help industrial leaders to implement data-driven decisions, this paper focuses on the survey of BDA and its applications in SM or SSM from a lifecycle perspective.

The paper is organized as follows: Section 2 introduces the search and screen method of the literature. Section 3 reviews the selected literature. Section 4 presents the original framework of BDA in SSM and explores the potential applications and key advantages of BDA in SSM. In Section 5, current challenges are discussed and suggestions for future research are provided. Section 6 highlights the contributions of the paper.

2. Literature search

The focus of this literature review paper was based upon answering the following five questions:

1. What are the characteristics of big data in current industrial communities?
2. What types of big data are needed or relevant in various lifecycle stages, for whom and when?
3. How is it possible to efficiently integrate and utilize the latest technologies to make big data more useful?
4. Which technologies can be used to efficiently measure, manage, extract and interpret the big data for usage in these evolving systems?

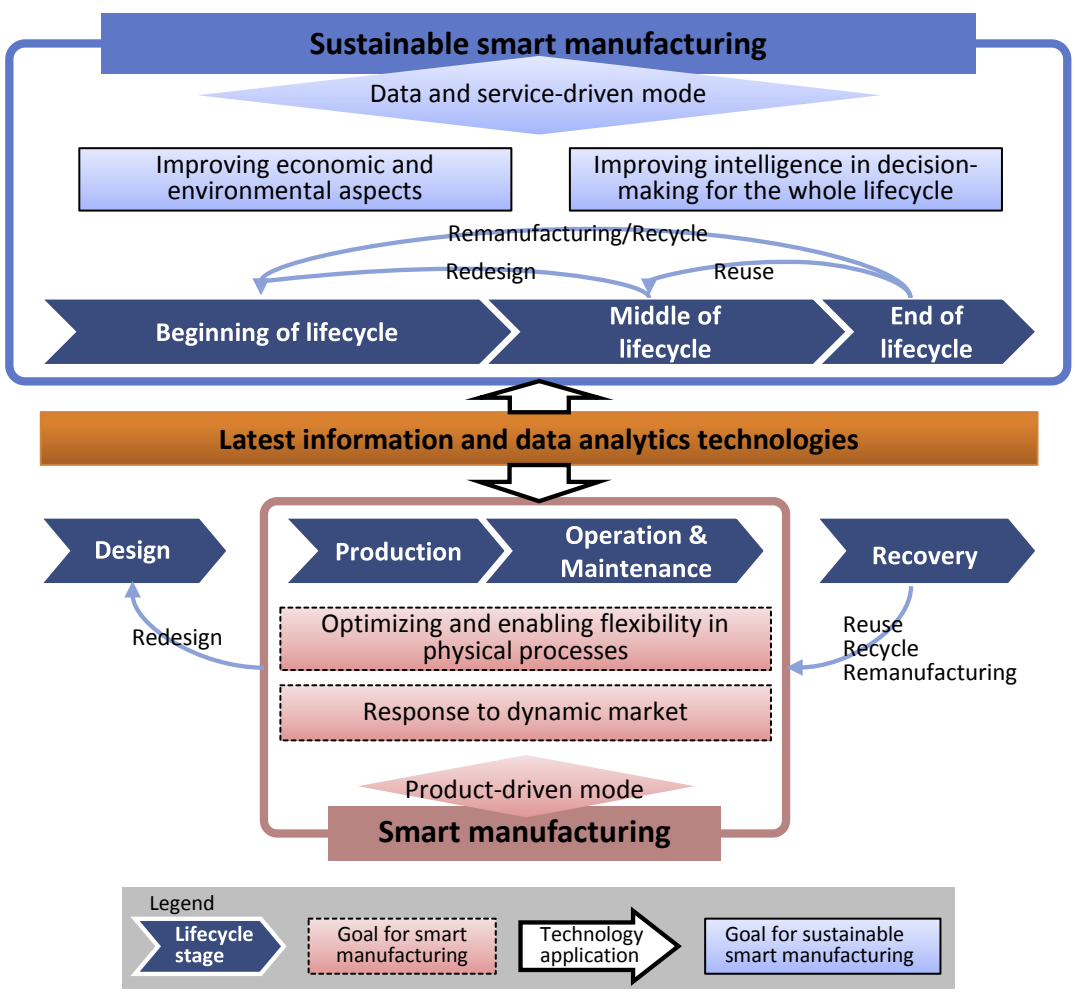

Fig. 1. Comparison of traditional SM and SSM.

5. What benefits can be gained by the involved industrial communities through applying the extracted information?

Based upon these five questions, a comprehensive literature review was performed through an iterative process of defining appropriate keywords, searching the literature and completing the analyses (Fahimnia et al., 2015). Nine search strings (Table 1) were designed to: use a broad range of keywords for comprehensively identifying the relevant literature. Then, the current state-of-art on corresponding topics was assessed to identify directions for future research, through scanning the bibliographic database, analyzing the selected literature, and building the bibliography (Fahimnia et al., 2015; Rowley and Slack, 2004). According to Tranfield et al. (2003) and Thürer et al. (2018), a systematic literature searching and screening methodology was used as follows.

The Scopus database was used because of its broader coverage. To keep the number of articles manageable, the search strings were limited to 'Article title, Abstract, Keywords' (Table 1), except for the first string – ("big data" AND (concept OR definition)) – that was restricted to 'Article title' to specifically locate articles related to big data's definitions. The Scopus database was queried separately by two authors in April 26, 2018, and the search for the nine strings resulted in identical results – a total of 3384 documents. To ensure the quality and the relevance of the documents, the search scope was further limited to peer-reviewed 'Article' written in 'English', published in the 'Engineering'. This refined the number of document results to 604, then reduced to 552 by removing duplicates, and further to 204 by excluding articles not referring to sustainability or smart manufacturing. Among the 204 articles, three were excluded since they had no citations two years after publication (Garfield, 2007), and the full text of 201 articles was downloaded and analyzed. In total, 76 articles were selected for detailed content analysis. The references of the 76 articles were checked, and 71 additional relevant documents were supplemented. This resulted in the final list of 147 documents that form the basis of this review paper. The searching methodologies and screening processes used in this study were summarized in Table 1 and Fig. 2, respectively.

In the modern industrial environment, data are key resources for business decisions. In order to build data-driven decision-support models to understand/interpret the insight of data, the methods of DM and AI as well as BDA were explored and used. With the objective of identifying the most significant studies and to determine the relevant areas of current research interest, the typical methods of DM/AI/BDA, and the application areas and shortcomings of these methods in different lifecycle stages were outlined and summarized as documented in Appendix A.

3. Overview of big data in smart manufacturing

This section is sub-divided into six subsections that review the concepts of big data in addition to its data classification criteria, architectures of big data in SM, key enabling technologies of SM and the applications of BDA in SM. In the final subsection, the authors highlight the knowledge gaps. The logic of the literature review based upon five questions was crucial to characterize the potential of lifecycle big data. The relationships among these questions, the literature review in the subsections and the derived knowledge gaps are depicted in Fig. 3.

3.1. Concepts of big data

The most cited definition of big data includes the 3Vs (Volume, Variety, and Velocity) theory introduced by Laney (2001), but organizations and researchers may have different concepts (Table 2). For instance, the IDC emphasized that big data should include 'Value' (Gantz et al., 2011), and IBM claim that big data should also have 'Veracity' (Zikopoulos et al., 2013). Two similar definitions were introduced by MGI (Manyika et al., 2011), Mashingaidze and Backhouse (2017) and Daki et al. (2017).

Definitions, technologies, modeling approaches and research

Table 1
Summary of searching methodologies used for this literature review paper.

Literature search strings	Search fields	Number of document results	Limit to	Number of refined document results
"big data" AND (concept OR definition)	Article title	91	Article, English	28
(lifecycle OR "product lifecycle") AND (information OR data OR "information flow" OR "data flow") AND (classify OR classification)	Article title, Abstract, Keywords	369	Article, Engineering, English	46
("big data" OR "big data analytics") AND (architecture OR framework) AND (manufacturing OR "smart manufacturing" OR lifecycle) AND (sustainable OR sustainability OR cleaner OR environmental OR energy)	Article title, Abstract, Keywords	71	Article, Engineering, English	9
("internet of things" OR IoT OR RFID OR "industrial internet of things" OR IIoT OR "industrial internet") AND ("green manufacturing" OR remanufacturing OR manufacturing OR production) AND (cleaner OR sustainable OR sustainability OR energy OR resource) AND (consumption OR efficiency OR efficient OR saving OR economy OR economical OR reuse OR recycling OR productivity)	Article title, Abstract, Keywords	599	Article, Engineering, English	130
("Cyber-physical" OR CPS OR "cyber-physical production systems" OR "cyber-physical sensor systems") AND (manufacturing OR production) AND (cleaner OR sustainable OR sustainability OR energy OR resource OR "service-oriented")	Article title, Abstract, Keywords	522	Article, Engineering, English	96
("cloud-based" OR "industrial cloud" OR "Cloud computing" OR "Cloud manufacturing") AND (manufacturing OR production) AND (cleaner OR sustainable OR sustainability OR "service-oriented")	Article title, Abstract, Keywords	392	Article, Engineering, English	71
"data mining" AND (manufacturing OR production) AND (cleaner OR sustainable OR sustainability OR "service-oriented")	Article title, Abstract, Keywords	150	Article, Engineering, English	17
"artificial intelligence" AND (manufacturing) AND (cleaner OR sustainable OR sustainability OR energy OR resource) AND (consumption OR efficiency OR efficient)	Article title, Abstract, Keywords	173	Article, Engineering, English	54
("big data" OR "big data analytics") AND (manufacturing OR (maintenance OR "supply chain") AND (cleaner OR sustainable OR sustainability OR service OR management)	Article title, Abstract, Keywords	1017	Article, Engineering, English	153
Total number of refined document results				604

Fig. 2. Summary of screening processes used for this literature review paper.

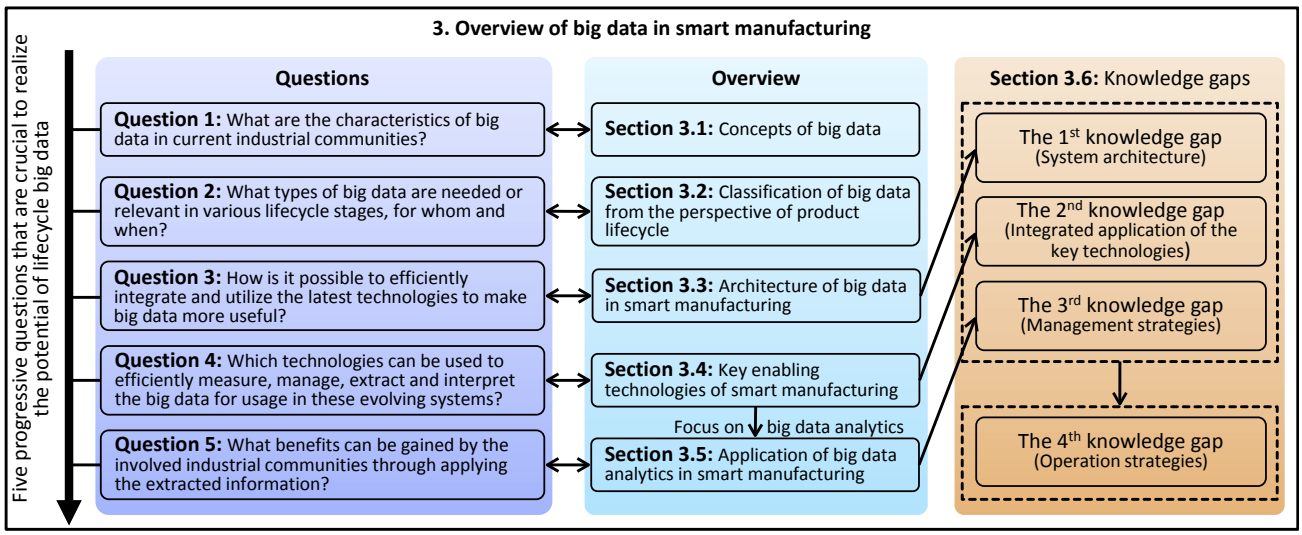

Fig. 3. Relationships among the five questions, the literature review in the subsections and the knowledge gaps addressed in this literature review paper.

challenges of big data from both industry and academic fields were discussed in the literature (Costa and Santos, 2017; Gandomi and Haider, 2015; Watson, 2014). In these articles, the characteristics of big data were analyzed by using some business cases from leading technology companies. The authors found that the popular concepts of big data were focused on predictive analytics and structured data. The largest component of big data, which is unstructured and is available as audio, images, video, and unstructured text was ignored by the leading technology companies. Finally, focused on the data in unstructured format, analytical methods and tools were discussed and recommended. Typical definitions of big data are presented in Table 2.

3.2. Classification of big data from the perspective of product lifecycle

Classification criteria of big data can highlight its attributes of interest and value to manufacturers. For example, what types of data are needed or relevant in various lifecycle stages, for whom and when? Data classification criteria can be applied as data preprocessing facets, because they can support the identification of required product-related data for lifecycle data tracking and feedback (Xu et al., 2009). They can be used to help industrialists to make decisions during different lifecycle stages (J. Li et al., 2015).

To clarify the multiple roles of data standards in PLM support systems and SCM, Liao et al. (2015) and Madenas et al. (2014) classified product-related data into spatial data, functional data and lifecycle data. A general model of data exchange between producers and consumers was developed to determine when to incorporate the available data, and to identify a suite of standards needed for supporting the exchange of product, process, operations and supply chain data. To facilitate appropriate data exchange and integration among OEMs and associated suppliers, Yang and Eastman (2007) categorized the lifecycle data as exchanging and

Table 2
Six representative definitions of big data.

Authors/organizations	Definitions or characteristics
Laney (2001)	Characterized by 3Vs theory, namely volume, variety, and velocity. Volume: with the generation and collection of masses of data, data scale becomes increasingly big; Velocity: timeliness of big data, specifically, data collection and analysis must be rapidly and timely conducted; Variety: the various types of data, which include semi-structured and unstructured data as well as traditional structured data.
Gantz et al. (2011)	Describes a new generation of technologies and architectures, designed to economically extract value from very large volumes of a wide variety of data, by enabling the high-velocity capture, discovery, and/or analysis.
Manyika et al. (2011)	Refers to datasets whose size is beyond the ability of typical database software tools to capture, store, manage, and analyze.
Mashingaidze and Backhouse (2017); Daki et al. (2017)	Includes data sets with sizes beyond the ability of commonly used software tools to capture, curate, manage, and process data within a tolerable elapsed time.
NIST (2012)	Means the data of which the data volume, acquisition speed, or data representation limits the capacity of using traditional relational methods to conduct effective analysis or the data which may be effectively processed with important horizontal zoom technologies.
Zikopoulos et al. (2013)	Big data contains four dimensions, namely volume, variety, velocity and veracity. Veracity: the unreliability and uncertainty inherent in some sources of data.

interoperable data, and proposed a rule-based subset generation method for product data modeling. The product lifecycle-related data were classified into generic types by Bouikni et al. (2008), including, product definition, product history, and best practice. Based on these researchers' findings, a three-dimensional data classification model was proposed by Xu et al. (2009). They were data changeability (static and dynamic), data characteristics (structured, semi-structured and unstructured), and product lifecycle stages (i.e. BOL, MOL and EOL). The authors recommended that the data classification standard to be firstly used to information structure modeling, and secondly to confirm which information can be acquired via wireless technology in different lifecycle stages. In order to integrate heterogeneous information systems in creating innovative products, the data classification standards of product data and product meta-data were discussed by Zehtaban et al. (2016). To achieve sustainable production, Kurilova-Palisaitiene et al. (2015) classified the product lifecycle data into six types, which included, product design specifications, manufacturing specifications, service specifications, original product quality assurance, core quality assurance, remanufactured product quality assurance.

3.3. Architecture of big data in smart manufacturing

The system architecture can be used to describe the layout of the whole system and the relationships among all components (Vikhorev et al., 2013). It can also be used to simplify the complex system management environment and to describe the complex procedures of lifecycle data sharing and knowledge interaction, and to ensure the validity of the entire system.

With the objective to explore the capacity of big data in product service, a framework of big data strategy in servitization for manufacturing enterprises was proposed (Opresnik and Taisch, 2015). Its impact on enterprises' SCA and value-creating were analyzed. By combining the design structure matrix and cladistics analysis, an architecture for minimizing energy consumption of a manufacturing system was synthesized (AlGeddawy and ElMaraghy, 2016). Results showed that energy consumption of the manufacturing system can be minimized throughout the production planning by system design. Dubey et al. (2016) performed an extensive literature review to identify different factors that enable the achievement of world-class sustainable manufacturing through big data. On this basis, a conceptual framework of sustainable manufacturing was proposed and tested by using a big data scenario. The factors that can facilitate the realization of sustainable manufacturing for academia and practice were emphasized. Based on data from service parts managers, a framework for application of big data in smart management of service parts was constructed and tested (Boone et al., 2017). By using that framework, the upstream challenges related to acquisition of service parts along with the downstream challenges related to service parts forecasting were analyzed. In view of existing research on the architecture of big data in manufacturing only focusing on one stage of the lifecycle (e.g. production stage of BOL and operation or maintenance stage of MOL), making difficult to effectively promote the improvement of lifecycle decision-making and the implementation of the CP strategy, Zhang et al. (2017b, 2017c) proposed an architecture of BDA for PLM to aid manufacturers to make better lifecycle and CP decisions. In this architecture, product servitization and BDA were effectively integrated. The effectiveness of the proposed architecture was tested via the analysis of processes of a turbo machinery manufacturer. Four managerial implications derived from the proposed architecture for the marketing department, the R&D department, the production department and the service department, were recommended to guide manufacturers to make better CP-related decisions in the whole lifecycle. To minimize energy and material usage while maximize sustainability of SM system, a big data driven sustainable manufacturing framework for condition-based maintenance prediction was developed (Kumar et al., 2018). In the framework, the condition-based maintenance optimization method was used to optimize the maintenance schedule and the backward feature elimination approach was used to eliminate the uncertainty of the remaining life predictions. In order to integrate IoT-based energy management data and company's existing information systems, a big data framework that including data collection, data management and data analytics layer was proposed (Bevilacqua et al., 2017). The proposed framework was applied in an Italian manufacturing company to assess its impact on improving energy efficiency. A framework of digital twin-driven product design, manufacturing and service with big data was investigated by Tao et al. (2018) and Zhuang et al. (2018) to help industry leaders to enhance the level of efficiency, intelligence, sustainability in product design, manufacturing, and service phases.

3.4. Key enabling technologies of smart manufacturing

Key enabling technologies of SM were developed to address data acquisition, transmission, storage, processing, analysis, knowledge and pattern discovery, which are major concerns in application of big data in SM. These enabling technologies can be used for maintaining the efficiency and sustainability of the SM system by providing reliable data and valuable insights for industrial leaders.

3.4.1. Internet of things and industrial internet

The IoT technologies have been widely applied in modern manufacturing, especially, in industrial emission and energy consumption monitoring (Hu et al., 2017; Martillano et al., 2017; Tao et al., 2014b). Due to the potential on data sensing, IoT was used to track the lifecycle data to improve recycling efficiency (Luttropp and Johansson, 2010; Tao et al., 2016) and to enhance product reuse rates (Ness et al., 2015). Ferrer et al. (2011) and Y. Zhang et al. (2018b) found that the implementation of IoT technologies can improve the operation efficiency of remanufacturing by at least 30%. In conjunction with sustainable production and green manufacturing, the IoT technologies were deployed at the machine and production-line level to collect the real-time energy consumption data of production processes. Subsequently, the IoT-based energy management system was developed and tested to improve energy-aware decisions of manufacturing companies (Yan Li et al., 2017; Shrouf and Miragliotta, 2015). The results showed that energy managers of a manufacturing company can utilize the IoT in a benefit-driven manner. Meanwhile, the method can also be used to address company's energy management and sustainable production practices. Jensen and Remmen (2017) analyzed how IoT technology can help OEMs (e.g. automobile, aircraft and ship manufacturers) to stimulate and implement high quality EOL product management strategies, and to support circular economy. The role of IoT in ensuring flexibility and resource efficiency for smart production system was investigated by Waibel et al. (2017). The potential smart innovations of IoT in technical, economic, social and environmental elements were discussed. Y. Zhang et al. (2018d) and J. Wang et al. (2018) explored the problems of multi-objective flexible job shop scheduling based on real-time IoT manufacturing data, and found that the usage of real-time IoT data for job shop scheduling can reduce the makespan, the total workload of machines and the energy consumption of the manufacturing system. The authors recommended that the IoT technology can contribute to sustainable CP of the manufacturing industry. Zuo et al. (2018) proposed a novel approach for product energy consumption evaluation and analysis based on IoT technologies, and tested its

effectiveness by using a case of a product's design and manufacturing processes. The results showed that the proposed approach can be used to enhance the intelligence of energy consumption evaluation and analysis, and to reduce energy consumption in product's design and manufacturing processes. An IoT-enabled real-time energy efficiency optimization method for energy-intensive manufacturing enterprises was explore by (W. Wang et al., 2018). Through a case study, the authors found that the IoT-enabled solution can be used to enhance energy efficiency and reduce environmental impacts.

As a highly integrated technology of advanced computing and analytics and sensors, the industrial internet was introduced by GE in 2012 to describe new efforts where industrial equipment such as wind turbines and jet engines were connected via networks designed to develop and share data and data processing for energy and transportation-based industries (Evans and Annunziata, 2012; Kelly, 2013). This approach aims achieving unification of industrial machines and software highlighting the similarity toward IoT and CPS as a technology focused framework (J. Q. Li et al., 2017). For example, through industrial internet, GE collects sensor readings from aircraft engines to optimize fuel consumption under diverse conditions (General Electric, 2014). Based on industrial internet, a new web-based system for real-time collaborations in adaptive manufacturing was developed (L. Wang, 2015). An assembly cell was used to verify and test the feasibility and the performance of the developed system. The results showed that the new system consumed less than 1% of network bandwidth than traditional camera-based methods, while the system can enhance the sustainability of manufacturing operations in decentralized dynamic environments.

Some industrial developers focused on connecting the physical and virtual world through the industrial internet and IoT to facilitate communication among connected entities (Gubbi et al., 2013). In this scenario, the term IIoT (Beier et al., 2018; Xu et al., 2014) was coined aiming to achieve the interconnectivity of industrial assets, such as machines, tools, and logistical operations. With the increased organizational complexity, communications among different production workers significantly impact the productivity of manufacturing organizations, especially for the SM environments. To determine the most economical communication technologies that can enhance productivity and sustainability in industry, Kareem and Adekiigbe (2017) examined traditional and modern communication technologies and their comparative advantages over one another in their adoption in manufacturing organizations. The findings suggested that the enhancement of productivity and the reduction of costs could be fully achieved by modern communication technologies (e.g. mobile-internet and industrial internet). One objective for adopting IIoT was to reduce resource consumption and fossil-carbon emissions of industrial systems. For this objective, a green IIoT architecture was proposed and tested to achieve energy-saving and to prolong the lifetime of the whole system (K. Wang et al., 2016). The authors designed a sleep scheduling and wake-up protocol to predict sleep intervals. Based on the predicted sleep interval, a simulation experiment for an activity scheduling mechanism to switch nodes to sleep/wake modes when required was developed to ensure the usage of the entire system resources in an energy-efficient way. The results documented significant advantages of the IIoT architecture in resource and energy consumption.

3.4.2. Cyber-physical system

The term CPS refers to the tight conjoining of and coordination between computational and physical resources with adaptability, autonomy and usability (Watanabe et al., 2016). In addition to CPS, there are several similar concepts, such as, CPPS (Miranda et al., 2017; Monostori, 2014; Wright, 2013), and CPSS (Berger et al., 2016).

In the context of industrial big data, the problems of modeling and virtualization for CPS were discussed by (Babiceanu and Seker, 2016). Lee et al. (2015b) proposed and tested guidelines for implementation of a CPS architecture in Industry 4.0 environment for integrating CPS in SM. The architecture was applied to machine tools in a production line, and the data and information flow were analyzed in detail. The authors provided viable guidelines for manufacturers to implement CPS to enhance product quality and system reliability with intelligent manufacturing equipment. The authors found that the CPS architecture not only can guarantee near zero downtime production, but also provide optimized production planning and inventory management plans. Additionally, focused on the trends of development of industrial big data, the impacts of CPS on maintenance and service innovation, and on the service-oriented manufacturing paradigm were investigated (Herterich et al., 2015; Lee et al., 2015a). To provide insights into addressing water resource sustainability challenges for industrial activities (e.g. manufacturing and energy production areas), an overview of water resource CPS for sustainability from four critical aspects (sensing and instrumentation, communications and networking, computing and control) was conducted by Wang et al. (2015). Recently, the sustainability of CPS-based production system (Song and Moon, 2017; Watanabe and Silva, 2017), CPS-based self-adaptive intelligent shop-floor (Zhang et al., 2017a), and CPS and big data enabled energy efficient machining optimization methods (Liang et al., 2018), were assessed and investigated. The authors found that the CPS-based approaches and technologies can be used to achieve improved, concerted function of collaborating systems, with enhanced adaptivity and autonomy of automation systems. Based on real-time manufacturing data, a framework of smart injection molding CPS was proposed (Lee et al., 2017). The framework integrated different types of data acquisition methods and decision-making rules. As a result, the authors suggested that the proposed framework can be used to enhance the competitiveness, sustainability and production performance of injection molding industry, and to support the construction of a smart factory.

3.4.3. Cloud-based technologies

Cloud computing was defined as "a model for enabling ubiquitous, on-demand network access to a shared pool of configurable computing resources that can be rapidly provisioned and released with minimal management effort or service provider interaction" (Mell and Grance, 2009). Cloud manufacturing as the manufacturing version of CC extends the philosophy of 'everything is a service' by adding new concepts as 'manufacturing resources as a service' (Tao et al., 2014a; Xu, 2012). Additional applications of cloud-based technologies in manufacturing have been developed by many researchers: the cloud-based approach for remanufacturing (Wang et al., 2014; Wang and Wang, 2014), cloud-based design and manufacturing (Stewart, 2006; Wu et al., 2015), and cloud-based energy-aware resource allocation approach and sustainable energy selection model (Peng and Wang, 2017; H. Zheng et al., 2017).

Effective management of the knowledge acquired during historical product design and development processes is one of the challenges facing many manufacturing enterprises. To address this challenge, a cloud-based product design knowledge integration framework was proposed by Bohlouli et al. (2011). The knowledge integration services can be provided for the collaborative product design procedure, and as a result, the sustainable and innovative product design and development pattern can be achieved. To address the challenges for managing the distributed manufacturing resources in supply chains, a cloud-based and service-oriented MES was developed (Valilai and Houshmand, 2013; Helo et al., 2014) showing that collaboration and data integration inside distributed

manufacturing were essential for success of supply chain solutions. Yue et al. (2015) developed a service-oriented industrial cloud-based CPS model, which integrated cloud technologies and CPS to improve the business services in Industry 4.0. With the support of the cloud and infrastructure platform as well as service application, industrial cloud-based CPS can improve manufacturing efficiency and enable a sustainable industrial system and more environmentally friendly businesses. The term of industrial cloud robotics was proposed to integrate the industrial robots resources worldwide and to provide manufacturing services for the end-users based upon a combination of cloud-based technologies and robotics (Liu et al., 2016). Energy consumption optimization for industrial cloud robotics was investigated, and a framework and its enabling methodologies of industrial cloud robotics towards sustainable manufacturing were developed. The authors suggested that the framework can be used to support energy-efficient services of industrial cloud robotics, and to realize sustainable manufacturing worldwide. On this basis, focused on the unified description of sustainable manufacturing capability of industrial cloud robots, a hybrid logic description method and an interval-state description method were proposed to jointly present the energy consumption during the industrial robots' processing (Y. Zhao et al., 2017).

3.4.4. Data mining

Due to the important role of knowledge acquisition from manufacturing databases, DM is being increasingly widely used in industry. A comprehensive analysis of DM applications in manufacturing and product quality improvement was conducted by Choudhary et al. (2009) and Köksal et al. (2011). Recently, the applications of DM in different lifecycle stages, such as product design (Kusiak and Smith, 2007), production (Cheng et al., 2018a), maintenance (Bennane and Yacout, 2012), fault diagnosis (Sim et al., 2014), service (Karimi-Majd and Mahootchi, 2015), and recycling (Y. Wang et al., 2016) were implemented.

The DM has also been attractive to many researchers on implementation of sustainable production and consumption strategies in manufacturing. Marwah et al. (2011) proposed an automated LCA approach based on DM to help the development of sustainable products. The authors recommended that manufacturers can use this approach to assess their design's sustainability in comparison with other designs. A supply chain quality sustainability DSS based on the association rule mining method was explored to support managers in food manufacturing firms to formulate logistical plans, and to maintain the quality and sustainability of the food supply chain (Ting et al., 2014). During the production stage, a DM method combining a SVM with a GA was developed by (J. Li et al., 2017) to quantitatively evaluate the effectiveness of CP. The proposed method was verified through a comparison in application, and the results showed that the GA-SVM method is more accurate and efficient than the back-propagation ANN. This study also suggested an effective assessment method for small samples of CP and provided a guideline for enterprise management on the implementation of CP for vanadium extraction from stone coal. Lieber et al. (2013) developed a systematic framework based on DM for predicting the quality of products in interlinked manufacturing processes using a rolling mill case study. The supervised and unsupervised DM methods were conjointly applied to identify the quality-related features and production parameters. The authors found that the proposed method contributed to achieve sustainable and energy-efficient manufacturing processes. Pang (2015) designed and tested an early warning system for the quality of complex products based on DM and NN theory aiming to reduce resource waste and increase productivity. The author suggested that the designed warning system could provide decision information that would not only help to improve existing products quality, but also aid in new product design. During the maintenance stages, the NN algorithms were applied to identify bearing faults in wind turbines (Kusiak and Verma, 2012), and an AD approach was tested to provide early failure warnings in rotating machinery (Purarjomandlangrudi et al., 2014). To enhance efficiency and reduce energy consumption of industrial robots in product disassembly processes, the industrial robot's disassembly capability was dynamically modeled by using the association rules mining algorithm (Z. Zheng et al., 2017).

3.4.5. Artificial intelligence

In recent years, diverse applications of AI have helped managers to make more effective decisions in manufacturing due to their capability to intelligently recognize and learn business models (Simeone et al., 2016). An AI-based CP evaluation system was developed to simplify the evaluation process of water consumption and environmental impacts of surface treatment facilities (Telukdarie et al., 2006). The potential benefits of AI for hybrid flow shop floor scheduling and energy consumption optimization were explored by Luo et al. (2013) and Ilsen et al. (2017), and a review of AI applications for supplier selection was conducted by Chai et al. (2013). Findings from these papers showed that most of the applications were focused on testing the algorithm for benchmarking or solving problems. Laalaoui and Bouguila (2014) and Çaliş and Bulkan (2015) assessed the AI application to pre-run-time scheduling in real-time systems and NP-hard job shop scheduling. Orji and Wei (2015) investigated a novel modeling approach that integrates fuzzy supplier behavior information with system dynamics simulation technique to help manufacturers to select the best possible sustainable supplier and to enhance the manufacturers' sustainability. The results of a simulation experiment showed that an increase in the rate of investment in sustainability by different suppliers causes an exponential increase in their total sustainability performance. Suganthi et al. (2015) applied fuzzy logic for modeling renewable energy systems to precisely map and optimize the energy systems. From the perspective of energy conservation, a new AI model, the multi-gene genetic programming, based on orthogonal basis functions was proposed to identify the hidden relationships between the energy consumption of the milling process and the input process parameters (Garg et al., 2015). Sensitivity and parametric analyses were conducted to validate the robustness of the model by revealing the potential relationships of energy consumption with respect to a set of input variables. The authors emphasized that, from these discovered relationships an optimum set of input settings for milling process can be obtained (e.g. cutting speed, feed rate and depth of cut). An AI-based DSS was developed by Shin et al. (2017) to improve the sustainability performance of manufacturing processes. Two case studies were used to show how to allocate resources at the production level and how to select process parameters at the unit-process level to achieve minimal energy consumption. Uncertainties in both the machine and the operating environments made the physics-based energy prediction models difficult to predict the energy consumption of the target machine reliably. To address this issue, Bhinge et al. (2016) and Oses et al. (2016) explored a modeling method based on the nonparametric machine-learning technique to optimize the energy-efficiency of a machining process. Commercial applications of AI were explored by Jacques et al. (2017) and McKinsey and Company (2017) to deliver new values such as smarter R&D and real-time forecasting, targeted sales and marketing, optimized production and maintenance to companies.

3.4.6. Big data analytics

BDA is the process of examining large and varied data sets to

uncover hidden patterns, unknown correlations, market trends, customer preferences and other useful information that can help organizations make more-informed business decisions (Abell et al., 2017; TechTarget, 2012), to improve sustainability and to drive the society towards the circular economy (Soroka et al., 2017). Applications of BDA have attracted attention from industry and academy due to the capability to provide valuable patterns and knowledge to increase BI, explore potential markets and improve operational efficiency (Lamba and Singh, 2017; Zhong et al., 2016). By deploying the BDA in the Cloud, conceptual frameworks of service-oriented DSS (Demirkan and Delen, 2013) were explored to improve QoS of the cloud. A BDA model was presented by Shin et al. (2014) to predict the sustainability performance, especially for power consumption of the metal cutting SM system. Furthermore, focused on the environmental concerns and the energy efficiency of modern industrial sector, a framework of energy monitoring and energy-aware analytics information system based on BDA was designed and tested (Zampou et al., 2014). To fully utilize the big data from production and energy management database to achieve a higher level of sustainability, manufacturers need methodologies for analyzing, evaluating, and optimizing sustainability performance metrics of manufacturing processes and systems. In this context, Shao et al. (2017) introduced a systematic decision-guidance methodology that used sustainable process analytics formalism and provided a step-by-step guidance for users to carry out sustainability performance analysis. The state-of-the-art and application landscape of BDA, as well as the impact of BDA on sustainable and green SCM and organizational performance were thoroughly investigated (Gunasekaran et al., 2017; Kaleel Ahmed et al., 2018). In these articles, research questions such as: In what areas of SCM was BDA utilized? At what level of BDA was used in SCM? What types of BDA models were used? were investigated in detail. Recently, focused on improving resource usage efficiency, the potentials of BDA in natural resource management and CP were investigated (Song et al., 2017a,b; Zhang et al., 2017c).

These key technologies of SM can be used for maintaining the efficiency and sustainability of SM systems. They can also be integrated and applied to facilitate the implementation of sustainable production and consumption strategies (Kusiak, 2017; Thoben et al., 2017). However, few studies have been done regarding effective integration and application of various key technologies of SM to implement these two strategies, not to mention even the use of these technologies for supporting the SSM paradigm.

3.5. Application of BDA in smart manufacturing

Manufacturers are being flooded by huge amounts of data, since various sensors, electronic devices, and digital machines are used in production lines and shop-floors (Zhong et al., 2017). According to MGI, companies embracing BDA are able to outperform their peers (Manyika et al., 2011). A survey from the EIU reported that many new opportunities and advantages can be created and gained through harnessing big data, in which the most compelling is increased operational efficiency (Fig. 4). It has been estimated that the combination of BDA and lean management could be worth tens of billions of dollars, in improved profits for large manufacturers (Dhawan et al., 2014; Ge and Jackson, 2014).

3.5.1. Illustrative examples

From the perspective of illustrative examples, Komatsu Ltd., a Japanese construction equipment manufacturer, has used BDA to assess the health status of the diesel engine component, and to provide remote fault prognostics services for its end-users (Lee et al., 2014). Every day, Siemens uses big data from 100,000 measurements in power plants around the world to implement remote diagnostic services to analyze the operational behaviors (Siemens, 2014). Similarly, Ramco Cements Limited, an Indian flagship manufacturer, leveraged BDA to make intelligent business decisions on product development and logistics management (Dutta and Bose, 2015). The SPEC, a leading eyeglasses manufacturer in China, analyzed the big data that were derived from customer feedback to provide ideas for new product innovations (Tan et al., 2015). Shaanxi Blower Group, a specialized turbo machinery manufacturer in China, established a product health management center that used sensor collected life-cycle big data to improve their service quality (Zhang et al., 2017c). Boeing's AHMS has been used to collect and analyze real-time big data of in air airplane operations and to notify ground crews of potential maintenance issues before landing (Boeing, 2017). To improve the sustainability of their supply chain, a Taiwanese light-emitting diode industry and a sanitary appliances manufacturer in China, used BDA to identify decisive attributes of SCRU, and to enhance their capability of GSCM (K. J. Wu et al., 2017; R. Zhao et al., 2017).

3.5.2. Theoretical research

From the perspective of theoretical research, Hofmann (2017) reported how BDA levers can reduce the bullwhip effect of supply chains, and which of them has the highest potential to do so. The BDA was utilized to address the challenges in industrial automation domain due to its capability of handling large volume of quickly generated data (Leitão et al., 2016). Hazen et al. (2016) and Papadopoulos et al. (2017) explored the role of BDA for supply chain sustainability, and Batra et al. (2016) and Jacobson and Santhanam (2016) highlighted its role on speeding up delivery time and improving R&D for semiconductor industry. To fulfill the potential of energy big data and to obtain insights to achieve smart energy management, a process model of BDA-based for smart energy management was proposed by Zhou et al. (2016). Furthermore, the impact of BDA on world-class sustainable manufacturing involving green product design and green production was explored by Dubey et al. (2016). In the SM environment, a smart spare parts inventory management system was proposed to establish transparency between manufacturers and suppliers and to reduce the inventory costs (Zheng and Wu, 2017). Through BDA, manufacturers can prepare spare parts for the right machine at the right time with the right quantity, and also optimizing the fuel use efficiency and the real-time route of spare parts transportation for suppliers.

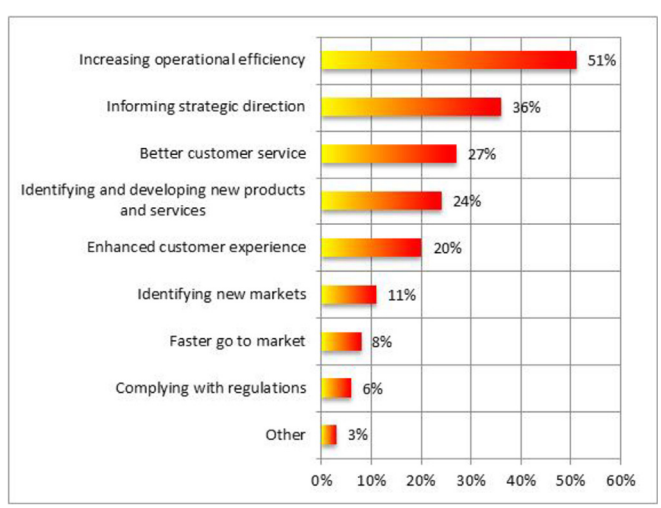

Fig. 4. New opportunities that BDA provides for commercial organizations to improve efficiency and effectively. Data source from (EIU, 2011; Tankard, 2012).

3.6. Knowledge gaps

With a focus on SSM and the previously highlighted literature, the following knowledge gaps for SSM are identified and described:

- Firstly, from the perspective of system architecture of big data in SM (Section 3.3), many researchers only focused upon one stage of the lifecycle (e.g. production stage of BOL and operation or maintenance stage of MOL). According to this analysis, to fulfill the SSM paradigm, a system architecture that covers the whole lifecycle stages is imperative. There is a lack of a holistic architecture for SSM paradigm that can be used to describe the complex procedures of the whole lifecycle data sharing and knowledge interaction, and the relations among various lifecycle stages.
- Secondly, there are various key technologies of SM, but as mentioned in the definition of SSM, to achieve the SSM paradigm, all these technologies should be integrated and applied in the operations and decision-making processes of the whole lifecycle. However, almost all research was focused on applying one or two of the latest technologies to improve and optimize the decision-making processes of specified lifecycle stages (Section 3.4). The research on effective integration and application of various key technologies of SM in the whole lifecycle decision-making processes to implement sustainable production and consumption strategies, and further to support the SSM paradigm was seldom conducted (Section 3.4.6).
- Thirdly, large amounts of process control and product performance data is generated in SM environment. As highlighted by Kusiak (2017), it is important to extract useful and valuable information from big data, and one of the most important methods in SM is BDA (Section 1). The BDA is also a promising method that can effectively facilitate the realization of the SSM paradigm, through deriving value from lifecycle big data, by implementing servitization strategies during the whole lifecycle, and by creating new added-value enhancing sustainability in manufacturing enterprises (Section 1). However, most research on BDA-enabled smart decision-making only involved limited lifecycle stages (e.g. production, maintenance, service stages), and do not focus upon usage of BDA in decision-making processes of the whole lifecycle to support the SSM paradigm (Section 3.5). Therefore, the third knowledge gap is that, in terms of management strategies, the research to effectively utilize the power of BDA for smarter decision-making processes of the whole lifecycle was rarely performed.
- Fourthly, the term SSM was derived from the traditional concept of SM. Because of its infancy, the SSM does not yet provide manufacturers with concrete operations strategies to enhance the visibility of their operations and the performance of all lifecycle business processes (Wamba et al., 2015). The insight into how to control and optimize the operations of the whole lifecycle management processes and service provision based on SSM is unavailable. However, this insight is required for implementation in industry and may have significant impact on the whole lifecycle' smarter decision-making and sustainability. Therefore, the insight related to how to control and optimize the operations of the whole lifecycle management processes and service provision, was identified as the fourth gap of SSM that is derived from the first three gaps (that will ultimately affect the effective implementation of SSM) and focuses on the operations strategies for SSM.

4. The framework of BDA in SSM

The overview presented in Section 3 was the basis for the conceptual framework, which was designed to help optimizing the lifecycle processes for sustainable production and CP. The framework is the first step to fill in all the knowledge gaps identified and presented in Section 3.6. This framework can be used as a guideline to select the most relevant lifecycle stages that affect the sustainable production of products of a specific enterprise, based on analysis of the available lifecycle big data. In this section, firstly, the framework of BDA in SSM is described. Then, using the proposed framework, potential applications and their key advantages were analyzed.

4.1. The conceptual framework of BDA in SSM

The goals of SSM for using the emerging information technologies and advanced analytics are: (a) to reduce resource waste; (b) to decrease environmental impacts; (c) to increase digitization level; (d) to achieve global intellectualization in manufacturing and service. To achieve these objectives in PLM, a conceptual framework of BDA in SSM was tested as presented in Fig. 5. This framework consists of four components from the perspective of product lifecycle stages: (a) intelligent design; (b) intelligent production; (c) intelligent maintenance & service; (d) intelligent recovery. For each component, the important elements (e.g. data flows, knowledge flows, main lifecycle stages, data sources and key lifecycle data) are described and analyzed in detail. The potential applications that will affect the realization of SSM are also involved in the framework. In subsections 4.1.1 to 4.1.4, the relationships among the key elements and the potential applications are briefly presented and analyzed.

What needs to be emphasized is that, within this framework, the sharing and feedback of lifecycle data not only can be achieved in their own interiors, but also can be realized among all lifecycle stages. The potential applications of this framework can only be achieved in every stage, when data sharing and feedback from other stages are realized. It is evident that as a result of sharing and feedback of data among all lifecycle stages, industrial leaders will be able to make more accurate and reliable lifecycle decisions, improving and optimizing the manufacture' production and management processes and facilitating the effective implementation of improvement options.

4.1.1. Intelligent design

The intelligent design component comprises market analysis, product and service design. In the market analysis stage, product

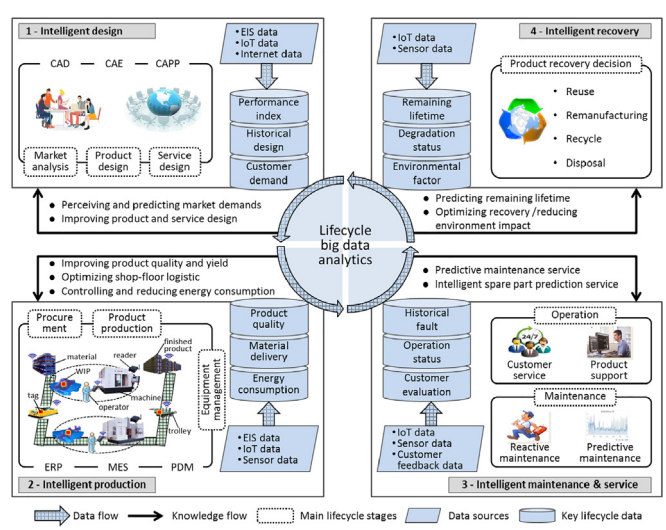

Fig. 5. Conceptual framework of BDA in SSM.

demand data provided by customers through Internet can be collected and analyzed. During product and service design stage, the RFID technology can be used for the management of technical documents (Jun et al., 2009). For example, the passive RFID tags attached to all technical documents enable technicians to manage huge numbers of technical documents in a systematic way. In addition, existing EISs such as CAD, CAE, and CAPP can provide valuable data support for product and service design. Therefore, the main data sources for this component are the Internet, IoT and EISs, while the key lifecycle data involves product performance indexes, historical product design and customer demands.

4.1.2. Intelligent production

The intelligent production component involves procurement, product production, and equipment management. In product production stage, all kinds of manufacturing resources (e.g. machines, operators, trolleys, etc.) are deployed with smart devices (e.g. RFID tags and readers, smart sensors and meters, etc.) to achieve a given degree of intelligence. The key parts are also equipped with smart devices that serve as mobile memory for the smart products, playing important roles throughout the assembly process and retained for subsequent processes of the lifecycle (e.g. logistic, maintenance, recycle, etc.). For equipment management, equipment fault diagnosis will influence the product precision and quality directly. The ERP, MES, PDM system, and fault diagnosis system can provide large amounts of data for intelligent production. These data are derived from EISs, IoT and sensors. In addition, the product quality, historical fault records, material delivery and energy consumption data can enhance effectiveness of sustainable production. For example, the product quality and historical fault records data can be combined and analyzed to firstly predict the failure and lifetime of the products in use, and secondly to assist the manufacturer to make a predictive maintenance planning. As a result, the reuse rate and use intensity of the products are improved. This can obviously reduce the total number of material and energy consumption. Furthermore, the material delivery data can be used to plan and suggest the real-time optimization route and to enhance the energy efficiency of shop-floor material handling.

4.1.3. Intelligent maintenance & service

The intelligent maintenance & service component consists of product operation and maintenance stages. Based on the deployment of the smart devices for products, real-time operation status data of smart products can be sensed and captured while used by the customers. For some products, not suitable for embedding smart devices, external smart devices are installed during the installation and debugging stages. The product operation stage mainly involves customer service (e.g. online consultation and personnel training) and product support (e.g. product quality monitoring and regular inspection), including corrective and predictive maintenance in product maintenance stage. Therefore, the real-time operation status data, product quality monitoring data, historical fault data and customer evaluation data that come from IoT, sensors, customer feedback and monitoring system present high potential for customer service, product support, and maintenance.

4.1.4. Intelligent recovery

In the intelligent recovery component, the only focus is how to make product recovery decisions. Owing to the configuration of the smart devices, the data related to product lifecycle history (e.g. remaining lifetime, degradation status and environmental factors) can be accurately gathered at the recycle stage. These data can play an important role in product recovery decision-making (e.g. reuse, remanufacturing, repair, recycle and disposal) and in reverse logistics planning. For example, based on the data of historical degradation status of a product, the identity information of RFID tags and smart sensors can provide unique identification code for subsequent classification of defective parts, which are separately sent to different take-back centers for further inspection and analysis. These historical IoT and sensor records can help inspectors to estimate costs and benefits of the various recovery operations within some constraints such as environmental regulations and product residual lifetime.

The following four steps can be used as a reference framework to select relevant lifecycle stages that impact the sustainable production of a given enterprise providing the enterprise manager the possibility to implement the framework. For clarification, no obligatory usage of the framework as a standard in industry is meant in this article.

1) According to different application requirements, the relationships presented in the framework will assist the managers to identify the main lifecycle stages that have significant effects on SSM.
2) Based on the identified lifecycle stages, the key indices and parameters that may impact the performance of a specified lifecycle's business processes can be identified.
3) According to the key indices and parameters that need to be improved and optimized, suitable lifecycle data, model and the appropriate algorithms can be selected and used to conduct the BDA.
4) Following the knowledge flow, including rules discovered through BDA, can provide important insights for managers to meet the application requirements to achieve SSM.

The major stages and potential applications of BDA in SSM are described in Fig. 5.

4.2. Potential applications and key advantages of BDA in SSM

Due to the increasing usage of leading-edge technologies in the modern manufacturing environment, data such as metrics for production processes, product operation and maintenance, etc., can be collected throughout the whole lifecycle. Through combining and applying BDA to all these lifecycle data, manufacturers can derive benefits, which are described in the following sections. What needs to be emphasized is that, all these advantages already are occurring for SM, which also can be framed by SSM.

4.2.1. Perceiving and predicting market demands

With the transformation of the production mode from mass to customized production, discovering customer preferences and demands has grown increasingly important for manufacturers. Accurately perceiving and predicting customers' preferences and demands are effective means for manufacturers to make their products better fit the needs of customers, and to earn higher loyalty and profit (Bae and Kim, 2011; Fang et al., 2016). By applying BDA, the massive volumes of data related to customer demands (e.g. online reviews and sentiments, customer behaviors and evaluations, and user experiences and feedback, etc.) can be collected and integrated from several sources for extracting actionable insights. These insights can be used to predict market demands in a timely mode, and the potential market size, margin, the number of competitors and the level of differentiation among products can also be predicted.

Although there are many factors that help to predict market demands, some factors are more important predictors than others. The use of BDA presents opportunities to identify the most important predictors of market demands, while manufacturers can closely monitor and analyze features, pricing strategies, and

customer feedback of their competitors' products. This information can help manufacturers to develop appropriate new product strategies.

4.2.2. Improving product and service design

The traditional product and service design methods scarcely consider the voices of other lifecycle stakeholders into the decision-making process systematically (Zhang and Chu, 2009). In the context of SSM, the isolated lifecycle data that influence the product and service design can be integrated and analyzed to generate important insights about product improvements and innovations. For example, based on the data gathered during the production, operation, maintenance and recovery stages (e.g. assembly requirements, product performances, customer evaluations, environment impacts, etc.), BDA can be used to discover relationships between lifecycle data and product innovation, and used to refine existing designs helping to guide the development of specifications for new products. These relationships can also assist designers to improve product design, such as design for maintenance/remanufacturing/environment (Dombrowski et al., 2014).

With the increasing competition and environmental pressures, manufacturers are striving to re-position themselves as solution providers by offering high value-added PSS (Song and Sakao, 2017). However, the design of PSS faces many challenges. For instance, design requirements and constraints at the schematic design stage are always imprecise, and alternative selection and matching at the decision stage are usually uncertain (J. Li et al., 2015). Manufacturers have found that BDA is an efficient tool for identifying the hidden requirements and improving the effectiveness of selection about multiple design alternatives. BDA helps to find the relationships among requirements, attributes and alternatives as exactly as possible to give comprehensive guidance for new PSS developments. Some manufacturers are inviting external stakeholders to submit ideas for innovations or to collaborate on PSS development. By applying BDA, the valuable ideas from a large number of submitted ideas can be extracted and thereby, the open innovation of PSS development can be achieved (Manyika et al., 2011; Zheng et al., 2018b).

4.2.3. Improving product quality and yield

Based on the configuration of smart devices, the real-time data of manufacturing resources (e.g. operators, materials, and WIP, etc.) can be tracked (Zhang et al., 2015). From the moment raw materials are delivered to the shop-floor to the moment the final products are packaged, there are dozens of quality control points deployed along the production line, and large quantities of data are produced. During operation and maintenance stages, the operation status and fault data can be used by manufacturers through BDA, to dramatically improve production and product quality.

Manufacturers can use BDA to find additional ways to reduce process flaws and to increase yields. For example, manufacturers can apply various data analysis models and algorithms to the production processes via usage of big data to determine interdependencies among process parameters, and their impacts on yields. The interdependencies can help manufacturers make better decisions in resetting parameters and in making targeted process changes that were found to have the highest impacts on yields. Additionally, BDA can be used to link equipment and process level data to inspection and metrology data to make more accurate predictions about yield failures. By identifying the factors responsible for failure, the BDA can help to reduce yield losses early in the production processes (Batra et al., 2016). Table 3 shows examples of applications of BDA in different industries for yield improvement.

Data source summarized from MGI (Auschitzky et al., 2014).

4.2.4. Optimizing shop-floor logistics

In SSM, IoT technologies are widely used to support the logistics management of warehouse and shop-floor, due to its capacity for real-time tracking the movements of manufacturing resources (Ren et al., 2018). In this context, large quantities of logistics data are generated from AGV, which can be used by internal and external logistics operators for improving logistics operations. In fact, for IoT-based SM, logistics planning and scheduling heavily rely on the arrival of materials, thus, the decisions on logistics trajectories (including crew and vehicle routing) are critical. The logistics big data of shop-floors can be harnessed to develop improvements in logistics planning. Through analyzing the historical and real-time logistics data, the frequent trajectories that have significant impacts on productivity and delivery time can be identified. This knowledge can be used to make more targeted logistics planning decisions. For example, the frequent trajectories knowledge can be used to determine the layout of distribution facilities (e.g. the distances between each pair of machines and tolerable traffic volume of shop-floor), the optimal routing of the vehicles (e.g. adjust the sequence of visited machines in shop-floor), as well as the best delivery and pickup time windows (Vidal et al., 2012). These can result in improvements of many manufacturing dimensions in the shop-floor, including yields, equipment availability, operating costs, delivery time, and energy consumption.

4.2.5. Controlling and reducing energy consumption

In today's manufacturing scenarios, energy conservation and emissions reduction are two important tasks for manufacturing enterprise. With the continuous application of smart sensors and smart meters during the whole lifecycle, large amounts of real-time energy consumption data from production and operation process can be collected (W. Wang et al., 2018; Y. Zhang et al., 2018c). The energy consumption data provide great potential to improve the decisions of energy efficiency management and to reduce energy consumption (Shrouf and Miragliotta, 2015). For example, based on the large quantity of energy consumption data gathered from inside and outside the shop-floor, and the correlation analysis among data, materials and energy flows, the decisions of collaborative optimization for energy consumption can be generated. By analyzing the data on a number of process parameters, those which have significant impacts upon energy consumption can be identified to establish a predictive model for the reduction of energy consumption. That model can be used to define strategies for optimizing the day-to-day energy consumption of manufacturing enterprises (Moreno et al., 2016). Because energy waste problems (e.g. water, electric and gas leakage) in manufacturing enterprises are usually unobservable, dangerous and costly, big data inputs can help managers to identify and quantify the wastage points and to reduce or eliminate them in real-time.

4.2.6. Providing predictive maintenance service and intelligent spare part prediction services

The IIoT paradigm promises to increase the visibility and availability of lifecycle data (Jeschke et al., 2017). Via IIoT, real-time data of the whole lifecycle can be gathered and analyzed, to improve maintenance and service decisions.

The product operation status data are gathered and transmitted to the manufacturer in real-time is an important asset for maintenance decisions. For example, by analyzing the product operation status data, manufacturers can evaluate indicators to determine whether equipment performance is decreasing. These analyses can help manufacturers to accurately predict when the products will fail, and early fault warning and predictive maintenance can be achieved. Operations and maintenance costs and equipment downtime can be reduced. A survey from MGI suggests that

Table 3
Examples of applications of big data in different industries for yield improvements.

No.	Industry	Current movements	Findings/solutions	Economic benefit/yield
1	Biopharmaceuticals	Monitoring more than 200 variables in the vaccines' production flow to ensure the purity of ingredients as well as the vaccines being made.	Nine parameters were documented to influence yield.Made targeted process optimization to take advantage of the nine parameters.	Increasing yield by more than 50%, and worth between $5 million and $10 million in yearly.
2	Chemical	Using BDA to measure and compare the relative impacts of different production inputs on yield.	The levels of variability in carbon dioxide flow prompted significant reductions in yield.Reset the parameters of carbon dioxide flow.	Reduced waste of raw materials by 20%, and reduced energy costs by 15%.Improving the overall yield.
3	Mining of precious metals	Examined the production process data of mining precious metals on a number of process parameters.	The best yield at the mine occurred on days in which oxygen levels were highest.Changed the leaching process, without making additional capital investments.	Increased yield by 3.7% and maintained a $10 million to $20 million in annual profits.

analyses of operation field data and provision of predictive maintenance services can reduce operational costs by 10%–25% while potentially boosting production by 5% or more (Manyika et al., 2011).

Through analyzing the data of the spare parts inventory, the consumption of spare parts can be dynamically predicted. Usage of BDA can significantly enhance the ability to predict failures for key spare parts, optimize transportation fuel efficiency, and suggest real-time route optimization (Boone et al., 2017). Therefore, intelligent spare part prediction services can be implemented and excessive production or excessive inventories can be avoided. These services can help manufacturers to transition to more sustainable production. For instance, by applying predictive maintenance service, the reliability of products can be increased and empty load energy consumption due to stopping and restarting of equipment and downtime can be reduced. By using the spare part prediction service, the inventory cost and material consumption can also be reduced.

4.2.7. Accurately predicting the remaining lifetime

It is clear that IoT technology can accurately gather data related to product lifecycle history (e.g. product design index, maintenance history, and operation status, etc.). Through analyses of the lifecycle data, the degradation status and remaining lifetime of products or parts can be predicted in real-time helping to make timely recovery decisions of EOL.

Although a complex product may not be useable any longer, that does not mean that every part of it is useless (Jun et al., 2009; J. Li et al., 2015). To prevent premature product obsolescence, it is important to predict the remaining value of parts. This issue highlights the need for BDA-based decision support. The predicted degradation status and remaining lifetime knowledge may benefit customers, manufacturers, and reduce environmental impacts. For customers, based on the discovered knowledge, sudden breakdowns of equipment can be effectively avoided contributing to enhance productivity and to reduce maintenance costs. For manufacturers, through providing accurate remaining lifetime information for its customers, the satisfaction and loyalty can be increased, more potential customers may be nurtured, and more profits can be created. Because manufacturers can be enabled to make better reuse and remanufacturing decisions, landfilling can be minimized, and negative impacts on the environment and humans can be reduced.

4.2.8. Optimizing recovery decisions and reducing environment impacts

Optimization of recovery decisions is regarded as a sustainable, environmentally friendly, and proven profitable practice in many developed countries (Abdulrahman et al., 2015). However, the optimizing process is not easy since a large amount of lifecycle data and historical lifecycle knowledge are needed and must be properly evaluated.

By analyzing the historical lifecycle data, the remaining lifetime of each part can be predicted. Consequently, optimal decisions of EOL product recovery can be made with the objective of maximizing values of EOL products (Jun et al., 2007). In this process, BDA-based decision-support mechanism provides opportunities for making good EOL recovery decisions. For instance, in order to help planning the remanufacturing processes, early identification and classification of defective components and their related data are essential (Y. Zhang et al., 2018b). By BDA, it may be possible to presort and prioritize components based on their historical lifecycle status, because some components may not need to be disassembled, and some may not be suitable for remanufacturing and hence must be replaced.

One of the major objectives of EOL product recovery is to reduce the environmental impact (Dat et al., 2012). Thus, it is necessary to ensure that the recovery process is energy saving and environmentally friendly. To achieve this goal, BDA should be applied to improve resource saving and recovery activities associated with minimizing resource consumption and reduction of risk to the workers engaged in the recovery processes.

5. Current challenges and future research directions

As highlighted by Koetsier (2014), by leveraging BDA across the value chain, more industrial dimensions can be systematically integrated, and the enterprise managers can be enabled to gather, store, process, visualize data to support intelligent and timely decisions. It is envisioned that future BDA applications will be able to assist enterprise managers to learn everything about what they did today and to predict what they will do tomorrow (Zhong et al., 2016). Although BDA has been broadly accepted by many organizations, as a new concept, the research on BDA in SSM is still in its early stages due to several key challenges.

To ensure that the current challenges are relevant to the previous literature review section and to guarantee the effectiveness of future research directions, two points need to be emphasized.

Firstly, the statements for the current challenges in this section were built upon the existing literature (Section 3). As a new scientific issue, the application of BDA in SSM, discussion and analysis of the challenges on its system architecture is critical and necessary (Section 5.1). In other words, a holistic architecture for capturing the business value in a systematic manner is the foundation to ensure the effective realization of SSM. Within a holistic architecture, the key technologies that have significant effects on SSM, mentioned in the previous literature review section, can be involved to ensure the effective implementation of SSM. Therefore, from Section 5.2 to Section 5.8, the challenges on these key technologies were discussed. These key technologies can be considered as two main subprocesses: data management (Section 5.2 to Section 5.5) and data analytics (Section 5.6 to Section 5.8). This conforms to the typical processes of extracting insights from big data, which are supported by Jagadish et al. (2014) and Gandomi and Haider (2015).

Secondly, all the statements for future research directions in this section were derived from the existing research and involved the authors' hypotheses. In addition to achieve the goals of SM, SSM is

also promising to carry out sustainable production and CP, through fusion of the strategy of servitization within all stages of product lifecycle. As highlighted by Opresnik and Taisch (2015), servitization has become a pervasive business strategy among manufacturers, because it can enable the manufacturers to reduce production costs and to achieve sustainable production. When analyzing the servitization practices of manufacturing enterprises and deriving more value from the servitization, some researchers found that data plays an important role (Sakao and Shimomura, 2007; Welbourne et al., 2009). In this regard, data management (Section 5.2 to Section 5.5) and data analytics (Section 5.6 to Section 5.8) are key technologies for SSM and important elements and enablers for servitization. As a result, the research directions related to these key technologies were considered as relevant research directions of SSM and were discussed in this paper.

5.1. Architecture of BDA for SSM

An optimal enterprise information IT architecture should be constructed to deal with historical and real-time lifecycle data at the same time, to benefit systematically from the business values that can be derived. Although there are many reference architectures for BDA, such as Hadoop (Borthakur, 2007) and Storm (Iqbal and Soomro, 2015), several challenges exist in the SSM field. Firstly, the isolated lifecycle data cannot be effectively collected and integrated into traditional IT architectures, and the management of unstructured data is often beyond traditional IT capabilities (Gandomi and Haider, 2015). Secondly, much architecture was built to deliver and analyze data in batches, so provision of the continuous flow of data for real-time data analysis and real-time lifecycle decisions is a challenge. Thirdly, according to different applications, only the observed and specific functional components, analysis methods and technologies were designed and included in existing architecture.

Therefore, the future of the BDA architecture in SSM needs:

- Various data and software interfaces, as well as related technologies (e.g. acquisition, preprocessing, management and storage) and functional components should be designed to acquire and integrate the whole lifecycle big data.
- Full analyses of the whole lifecycle data are not likely to be feasible in real-time decisions. One effective means is to find elements in large datasets that meet specified criteria (Jagadish et al., 2014). Therefore, new data index structures and data analysis methods should be created in the architecture to quickly and effectively find a variety of qualifying elements, and to provide reliable data support for accurate and almost real-time lifecycle decisions.
- A robust and scalable IT architecture to support various application requirements and optimization tasks for all lifecycle stakeholders (Hu et al., 2014). If the architecture is extended, in the future, based on other BDA applications, it should be designed to be scalable with new functional components or relevant technologies.

5.2. Data quality management for SSM

Monitoring and controlling of data quality during all lifecycle processes are important for manufacturers to perform BDA, and to make better SSM and servitization related decisions. As emphasized by Wamba et al. (2015), the availability of good quality of big data is crucial to add value to the organization. Poor quality data have little potential to assist managers to make correct decisions, wasting organizational resources and adding data storage costs (Cynthia et al., 2012). As the quality and quantity of lifecycle data are enhanced, they can be used to improve business models and decisions as well as servitization processes. However, there is the risk of inconsistent and incomplete data, which may undermine service delivery and decision-making processes. Therefore, poor data quality and ineffective data management in the whole lifecycle are key challenges to be solved for effectively applying BDA in SSM.

Future perspectives of the data quality management in SSM should focus on the following aspects:

- With the goal of improving data quality and the decisions based upon the data, the theories of RBV and KBV (Hazen et al., 2014) should be investigated to enable continuous monitoring mechanisms and ensure that future lifecycle data acquisitions are properly managed.
- The tools of data quality management such as process capability analyses (Veldman and Gaalman, 2014), and statistical process control chats (Jones-Farmer et al., 2014) should be investigated and used to improve data quality during the lifecycle of data acquisition, storage and usage.
- The theories of managing and querying probabilistic and conflicting data (Jagadish et al., 2014) should be further explored to manage and correct the incompleteness and inconsistency in the lifecycle data.

5.3. Data acquisition

All decisions related to SSM are based on whole lifecycle data. In spite of the fact that there are multiple data acquisition methods such as Auto-ID technologies and smart sensors, accurate and complete acquisition of the whole lifecycle data in a timely fashion continues to present large challenges for SSM field (Zhong et al., 2013, 2016). Firstly, manually-based data acquisition approaches are still widely used in some lifecycle stages, especially in the design, maintenance and recovery stages. The data acquired from these approaches are usually inaccurate and untimely, thus, decisions based on such data are usually ineffective. Secondly, for the majority of traditional products, such as machine tools, the data flow usually breaks down after the delivery of products to customers and the products are always used in different conditions. Therefore, the real-time, accurate, and complete data acquisition for MOL and EOL stages is a challenge that must be addressed.

To address these challenges, further research on data acquisition in the whole lifecycle should be conducted as follows:

- The RFID must be utilized more effectively in the management of technical documents in the design stage. For example, the passive RFID tags can be attached to all technical documents to manage large quantities of technical documents in a systematic way and thereby, reduce unnecessary errors. In addition, the RFID device can be used as a mobile memory to record and update the real-time degeneration status and lifetime data of components in the EOL stage (Jun et al., 2009).
- To use smart mobile devices to collect the real-time field data. For example, IoT technologies can be embedded into the physical products with the functionalities for gathering the lifecycle data. In addition, the multi-functional, wireless or contactless, as well as much smarter data acquisition devices, such as wearable devices with intelligence (C. H. Wang, 2015; Zheng et al., 2018a), should be designed to capture product-related data under extreme environments, such as high temperatures, high pressures, toxic, and high nuclear radiation environments.

5.4. Data integration and aggregation

An effective decision of SSM requires the collection of heterogeneous lifecycle data from multiple sources. In SSM, software tools and systems used by all departments and lifecycle stages should be integrated so that the whole lifecycle data can be shared promptly and correctly among all stakeholders (Zhang et al., 2017c). However, diverse data acquisition devices, software tools and systems have their own specific data formats, which are commonly heterogeneous, unstructured, and incompatible. Integration and aggregation of the whole lifecycle data for effective SSM decision-making, urgently needs in-depth research, development and testing.

Future data integration and aggregation must be performed in two dimensions related to the data meta-models and middleware technologies:

- An unified data modeling method can be used to construct the multi-granularity and multi-level data models (Petrochenkov et al., 2015), and to integrate the data of various lifecycle stages. The concept of the meta-model must be developed and integrated to build the unified data models. From the perspective of product lifecycle, design, production, maintenance and recovery data meta-models should be developed and utilized (Zhang et al., 2017b).
- In the future, much smarter middleware technologies and methods, such as IoT middleware (Ngu et al., 2017) must be developed to transform raw lifecycle data into a standardized format and meaningful information for all lifecycle stakeholders to use. The smart middleware must provide functions for data cleaning, semantic data filtering, data aggregation and active data tracking.

5.5. Application of cloud-based techniques in SSM

Besides having the capability of large-scale computing, the cloud-based techniques can provide the storage capability for the whole lifecycle big data (Tao et al., 2017). However, there are several challenges involved in applying cloud storage in SSM. Firstly, the security and privacy should be addressed. For example, the lifecycle data may contain sensitive data of customers, suppliers and manufacturers, and the tools to make use of these data may give rise to unauthorized access. Secondly, query optimization is needed to harvest the knowledge hidden in the lifecycle big data. Improved methods of optimized query pertaining to energy consumption and fast processing time are essential.

Therefore, future application of cloud-based techniques in storage of lifecycle big data for SSM should be focused upon the following aspects:

- New safety tools should be developed and implemented to improve the security of cloud-based storage mechanisms. This may be achieved by leveraging conventional security mechanisms in combinations with new technologies, such as Apache Accumulo (Zareian et al., 2016). In addition, the development of human-computer interaction techniques (Xu, 2012) should attract researchers' attention, to help security analysts to convey information to customers' formats, that are easier to utilize.
- In the future, the criteria to support partial query optimization must be refined so that a small amount of incremental computation with new data can be used to facilitate quick and effective decision-making processes. Therefore, seeking to develop systems with suitable interactive response times (Jagadish et al., 2014) in querying complex, high-volume lifecycle data is urgently needed. Additionally, parallel computing mechanisms (Catalin et al., 2012) should be developed to provide effective methods for query processing in cloud-based storage environments.

5.6. Models and algorithms of BDA-based decisions for SSM

The decisions in SSM require relevant knowledge that could be discovered from the whole lifecycle big data. Currently, the traditional DM and AI models and algorithms are being updated by many researchers, and are called BDA-based decision approaches (Zhong et al., 2016). However, many existing models and algorithms cannot meet the challenges in applying of BDA to SSM. Firstly, the decision models of SSM may need large amounts of data for mining knowledge for various lifecycle applications in real-time (e.g. such as shop-floor scheduling and predictive maintenance). However, many algorithms are not suitable for analyzing large numbers of data sets, in a timely mode. Secondly, current decision-support models always operate in isolation to analyze the given data of a specific lifecycle phase, to solve specific lifecycle problems. Generic models that can analyze the whole lifecycle data for solving multi-objective problems have been seldom considered.

New methods can provide answers to these challenges by developing BDA-based decision models and algorithms for SSM in two directions:

- The self-adaptive and self-learning models that have the capability of learning from massive data for evolving in timely and continuous processes should be developed (Zhang et al., 2017a; Zhu et al., 2018). The deep learning theories should be integrated into decision-support models so that real-time and automated analyses can be achieved.
- The mixed-initiative learning models, based on the idea of collaborative decisions (Stefanovic, 2015) are required. New decision-support mechanisms must be designed to work collaboratively with various lifecycle experts to jointly analyze massive quantities of data, based upon diverse knowledge to make more informed lifecycle decisions.

5.7. Application of complex network theory in SSM

Applications of complex network theory in SSM can provide a more effective way to solve complicated lifecycle management problems due to the increasingly ubiquitous connections of manufacturing resources and products. For example, in the product design stage, complex network theory can be used to reveal the complicated relationships between products and parts (Y. Li et al., 2017), products and services, as well as the data and knowledge flow in/among enterprises, to achieve collaborative innovation and design. Such complex networks are being used to explore the relations between and among workstations, to manage manufacturing services and supply chains (Qin et al., 2011; Kim et al., 2015; Cheng et al., 2017). Despite its theoretical successes, complex network theory remains young with many challenges. Firstly, although complex networks can analyze diversified network structures, networks intertwined in complex SMM environments, continue to be key challenges. Secondly, the applications of complex networks in manufacturing mostly focus on the exploration phase. The integration of phases such as the feedback and collaboration mechanisms among different lifecycle stages in real-time have not yet been solved.

Future directions for research on complex networks in SSM include:

- New approaches that effectively integrate collaboration of complex networks built by different lifecycle stakeholders. These may include more appropriate network models, such as hyper-networks (Cheng et al., 2018b) designed to monitor the interactions and influences among multi-layer networks.
- Development of network models for real-world usage to obtain solutions for desired objectives in SSM. More advanced algorithms based on BDA for network construction should be designed. To achieve the objective of dynamic optimization of supply and demand matching of manufacturing resources and allocation of manufacturing services (G. Zhang et al., 2018), dynamic network evolution models based on the real-time lifecycle data are needed.

5.8. Energy-consumption analysis and optimization of SSM

Green, energy saving, and sustainable production and consumption of renewable energy are major objectives of the SSM. Energy-consumption analysis and optimization of the whole lifecycle is a key issue for realizing green and sustainable production and consumption (Santos et al., 2011). To realize energy-consumption optimization in SSM, several challenges must be addressed. First, with the help of lifecycle big data, models or algorithms of energy-consumption analysis and optimization for various lifecycle stages must be established. However, the data-driven models do not have evaluation criteria and index to assess efficiency and effectiveness (Zhong et al., 2016). Then, in SSM environments, the availability of energy-consumption related data can be greatly enhanced due to continuous energy usage monitoring and tracking. This has highlighted the need for establishing an intelligent energy-consumption management system for SSM.

To address these challenges, two research directions are recommended:

- Energy-consumption evaluation criteria and index systems should be developed for diverse lifecycle stages. Multi-objective energy-consumption evaluation index systems with flexibility and variability of material/energy/data flow (Hou et al., 2016) in the whole lifecycle should be developed and tested in real-time systems.
- To achieve intelligent energy-consumption decision-making, an energy cyber-physical ecosystem (Palensky et al., 2014) should be developed to monitor and manage the interactions and influences of energy usage among various lifecycle stages. Data on these interactions can be delivered to cyberspaces to achieve real-time monitoring and dynamic optimization of energy efficiency.

The current challenges for SSM from the perspective of product lifecycle were briefly summarized and are listed in Table 4.

6. Conclusions

As a new networked and service-oriented manufacturing paradigm, the SM has experienced rapid development in recent years. The objective of developers of SM is to help managers to make more efficient, profitable and sustainable decisions. Within the SM environment, the emerging technologies such as IoT, sensors and wireless technologies are being increasingly used by industrial leaders to capture and utilize data in all stages of the product lifecycle. Consequently, a large amount of multi-source and heterogeneous datasets are being collected and used for supporting lifecycle decision-making. Among a large variety of key technologies for SM, the BDA was considered as one of the most important technologies, due to its capacity to explore large and varied datasets to uncover hidden patterns and knowledge as well as other useful information. The discovered patterns and knowledge can help industrial leaders to make more-informed business decisions, and to achieve the whole lifecycle optimization and more sustainable production.

The literature review revealed that BDA and SM have been individually researched in academia and industry, but the research into simultaneously applying BDA to SM is still in its infancy. To address these limitations, the authors provide insights for future research in this field. The following significant contributions were made by the authors of this review:

- Firstly, by combining the key technologies of SM with the concept of ubiquitous servitization at all lifecycle stages for intelligent and sustainable production, the term SSM was coined and used throughout this paper. This concept did not exist in a clear form before but it is crucial to advance knowledge in this area, Therefore, the definition of SSM was given, and the differences between this definition and Industry 4.0 and SM were highlighted.
- Secondly, a comprehensive review of big data in SM was conducted. The concepts of big data and data classification criteria, system architectures, key technologies of SM, and applications of BDA in SM were characterized in detail. Four knowledge gaps were identified, and the insights from the literature on typical DM, AI and BDA methods in different lifecycle stages were summarized.
- Thirdly, from the perspective of product lifecycle, a conceptual framework of BDA in SSM was proposed. The framework can be used as a guideline to select the relevant lifecycle stages that impact the sustainable production of a given enterprise. The potential applications and key advantages of BDA in SSM were discussed.
- Finally, current challenges and future research directions, which should identify relevant future research directions in academia and in industry were discussed.

Table 4
Current challenges for SSM from the perspective of product lifecycle.

Current challenges	Product lifecycle			
	Design	Production	Maintenance/service	Recovery
Architecture of BDA for SSM	✓	✓	✓	✓
Data quality management for SSM	✓	✓	✓	✓
Data acquisition	✓	✓	✓	✓
Data integration and aggregation	✓	✓	✓	✓
Application of cloud-based techniques in SSM	✓	✓	✓	✓
Models and algorithms of BDA-based decisions for SSM	✓	✓	✓	✓
Application of complex network theory in SSM	✓	✓		
Energy-consumption analysis and optimization of SSM	✓	✓	✓	✓

Both academics and industrial leaders will obtain insights from the summary of the major lines of research in the field. Future work should be focused upon ways to improve the proposed framework by considering a wider range of applications of BDA in product lifecycle for sustainable production and CP. In addition, other key technologies related to SM should also be investigated. The authors solicit reader's feedback and suggestions for cooperation and collaboration in this rapidly evolving array of approaches to help making quantitative and qualitative improvements in all societies.

Acknowledgements

The authors would like to acknowledge the financial supports of National Natural Science Foundation of China (51675441), the Fundamental Research Funds for the Central Universities (3102017jc04001) and the 111 Project Grant (B13044). This research was also supported in part by the Circularis (Circular Economy through Innovating Design) project funded by Vinnova - Sweden's innovation agency (2016-03267) and the Simon (New Application of AI for Services in Maintenance towards a Circular Economy) project funded by Vinnova - Sweden's innovation agency (2017-01649).

Appendix A. The research of typical data mining, artificial intelligence, and big data analytics methods in product lifecycle management

Lifecycle stages	Lifecycle sub-stages	Typical methods			Applications	Shortcomings
		Data mining	Artificial intelligence	Big data analytics		
Design	Customer requirements identification	Fuzzy clustering, fuzzy association rule mining (Jiao and Zhang, 2005; Li et al., 2013); Apriori, C5.0 DT (Bae and Kim, 2011; Ma et al., 2014)	ANN, back propagation (Efendigil et al., 2009; Lee et al., 2011); bootstrap aggregating, PCA (Liu et al., 2013)	Autoregressive integrated moving average model (Jun et al., 2014); web crawling and NN (Chong et al., 2017); Kalman filter and Bayesian (Jin et al., 2016); hierarchical multiple regression (B. Li et al., 2016)	Consumer electronics, furniture/jewelry/ hybrid car industry	Many researches focused on e-commerce. Fewer studies involved in industrial products field.
	Design scheme configuration and optimization	C4.5, association rule mining, NSGA-II (Fung et al., 2012; Geng et al., 2012); fuzzy clustering, RST (Hong et al., 2010); K-means and AdaBoost classification (Lei and Moon, 2015)	Hybrid PSOA (Tsafarakis et al., 2013); ABC (Renzi et al., 2014; Chen and Xiao, 2015); BPNN, fuzzy regression (Kwong et al., 2016)	ABS and ANN (Afshari and Peng, 2015; Kutschenreiter-Praszkiewicz, 2013)	Automobile, hybrid rocket engine, gear box, electrical bicycle, printed circuit board, steel and chemical industry	The methods of BDA were seldom investigated. Many researches were based on the traditional AI methods.
Production	Shop floor scheduling	Attribute induction algorithm (Koonce and Tsai, 2000); C-fuzzy and DT (Shahzad and Mebarki, 2012)	SA, TS, VNS, ACO (Lee, 2007; Çaliş and Bulkan, 2015); ANN and RBFN (Mehrsai et al., 2013)	Max percentages, Min-Min and Sufferage algorithm (X. Li et al., 2016); GA, NSGA-II and MapReduce (Lu et al., 2016); RapidMiner platform and DT (Ji and Wang, 2017)	Automotive industry, rotary injection molding industry	Most literature were theoretical and simulated studies, the industrial applications were fewer involved.
	Quality control	K-means clustering, fuzzy C-means clustering, association rule mining, SVM (Da Cunha et al., 2006; Köksal et al., 2011); PCA, EM (Zhang and Luk, 2007); regression DT, KNN (Ferreiro et al., 2011)	Grey relational analysis, GA (Aksu et al., 2013; Sibalija et al., 2011); role-based context-specific Q-learning algorithm (Mahdavi et al., 2013); case-based reasoning and fuzzy logic (Choy et al., 2016)	Multilevel stratified spatial sampling (Xie et al., 2015); MapReduce framework and radial basis function-based SVM (Kumar et al., 2016)	Automotive, plastic injection molding, printed circuit board, steel/ chemical/cement industry	New methods relevant to BDA were fewer. Most researches focused on process manufacturing, the discrete manufacturing was fewer considered.
Maintenance & service	Fault identification and diagnosis	NN, boosting tree algorithm (Kusiak and Verma, 2012); AD and SVM (Purarjomandlangrudi et al., 2014); k-medoids algorithms (Demetgul et al., 2014); associated frequency pattern tree (Rashid et al., 2016)	PSOA, extended Kalman filter (Nyanteh et al., 2013); random forest fusion, SVM (Jia et al., 2016; C. Li et al., 2015); SVM regression (Gururajapathy et al., 2017)	Classification and regression tree (Chien and Chuang, 2014); sparse filtering of NN, softmax regression (Lei et al., 2016); Storm, Spark platform and SVM (Wang and Zhang, 2017)	Automotive, semiconductor manufacturing, gearbox, rotating machinery, motor bearing	Lacking of the combination of BDA and other intelligent algorithms in current researches.
	Predictive maintenance	Apriori, C5.0, Boosting (Raheja et al., 2006; Unal et al., 2016); clustering and RST (Magro and Pinceti, 2009); EM, linear regression (Onanena et al., 2010)	SVM, KNN (Nadakatti et al., 2008; Susto et al., 2015); NN auto regression, feed-forward back propagation ANN (Lam and Oshodi, 2016; D. Wu et al., 2017)	PCA, DT, clustering (Li et al., 2014; Lee et al., 2015a); roughness-induced pavement vehicle interaction model, deflection-induced model (Louhghalam et al., 2017)	Fuel cell, bearings, semiconductor device, milling tool, rail and road network	The methods of BDA in this stage were scarce. Most literature were theoretical and experimental studies, industrial applications were fewer involved.
	Improve the QoS	DT, association rules mining (Huang and Hsueh, 2010); dominance-based rough set and DOMLEM algorithm (Liou et al., 2011); classification and regression trees (De Oña et al., 2012)	Multilayer perceptron ANN, fuzzy inference (Hsieh, 2011)	Logistic regression, SVM, and Hadoop platform (H. Li et al., 2015); PageRank, AuthorRank and MapReduce framework (Sun et al., 2015)	Airport, tourist, computer and social networks, traffic, telecom	Many researches focused on tourist, traffic and telecom industry, the QoS for industrial products field was concerned rarely.

(continued on next page)

(*continued*)

Lifecycle stages	Lifecycle sub-stages	Typical methods			Applications	Shortcomings
		Data mining	Artificial intelligence	Big data analytics		
	Spare part service	K-means clustering, association rule mining (Kargari and Sepehri, 2012; Moharana and Sarmah, 2016)	Fuzzy logic, grey theory (Zeng and Wang, 2010); ANN, multiple regression (Kumru and Kumru, 2014)	BI semantic model, clustering, NN, DT (Stefanovic, 2015)	Automotive, nuclear power plant, metal industry	The methods for this stage were seldom developed. Studies of BDA on this topic were just theoretical researches, the engineering applications were almost vacant.
Recovery	Remanufacturing and recycling	C4.5, preference trend mining algorithm (Ma et al., 2014); text mining, clustering, regression (Mashhadi et al., 2016; Mashhadi and Behdad, 2017)	GA and inverted tree (Smith et al., 2012); PSOA, GA (Guo and Ya, 2015); KNN, fuzzy RBFN (Roh and Oh, 2016)	Game theoretic, Bertrand model, Stackelberg model (Niu and Zou, 2017)	Electronic products, gear reducer, chemical industry	All three methods have rarely researched at EOL stage, especially for BDA. The methods for BDA in this stage were almost vacant.

References

Abdulrahman, M.D.-A., Subramanian, N., Liu, C., Shu, C., 2015. Viability of remanufacturing practice: a strategic decision making framework for Chinese auto-parts companies. J. Clean. Prod. 105, 311–323.

Abell, J.A., Chakraborty, D., Escobar, C.A., Im, K.H., Wegner, D.M., Wincek, M.A., 2017. Big data-driven manufacturing—process-monitoring-for-quality philosophy. J. Manuf. Sci. Eng. 139, 101009. https://doi.org/10.1115/1.4036833.

Afshari, H., Peng, Q., 2015. Modeling and quantifying uncertainty in the product design phase for effects of user preference changes. Ind. Manag. Data Syst. 115, 1637–1665. https://doi.org/10.1108/IMDS-04-2015-0163.

Ahn, G., Park, Y.J., Hur, S., 2017. Probabilistic graphical framework for estimating collaboration levels in cloud manufacturing. Sustainability 9. https://doi.org/10.3390/su9020277.

Aksu, B., Paradkar, A., De Matas, M., Özer, Ö., Güneri, T., York, P., 2013. A quality by design approach using artificial intelligence techniques to control the critical quality attributes of ramipril tablets manufactured by wet granulation. Pharm. Dev. Technol. 18, 236–245. https://doi.org/10.3109/10837450.2012.705294.

AlGeddawy, T., ElMaraghy, H., 2016. Design for energy sustainability in manufacturing systems. CIRP Ann. Manuf. Technol. 65, 409–412. https://doi.org/10.1016/j.cirp.2016.04.023.

ASTM International, 2017. Products and Services/Standards & Publications/Journals/Smart and Sustainable Manufacturing Systems. https://www.astm.org/SSMS/ssms_about.html (accessed 2018.03.29).

Auschitzky, E., Hammer, M., Rajagopaul, A., 2014. How Big Data Can Improve Manufacturing. https://www.mckinsey.com/business-functions/operations/our-insights/how-big-data-can-improve-manufacturing (accessed 2017.05.17).

Babiceanu, R.F., Seker, R., 2016. Big Data and virtualization for manufacturing cyber-physical systems: a survey of the current status and future outlook. Comput. Ind. 81, 128–137.

Bae, J.K., Kim, J., 2011. Product development with data mining techniques: a case on design of digital camera. Expert Syst. Appl. 38, 9274–9280.

Batra, G., Jacobson, Z., Santhanam, N., 2016. Improving the Semiconductor Industry through Advanced Analytics. https://www.mckinsey.com/industries/semiconductors/our-insights/improving-the-semiconductor-industry-through-advanced-analytics (accessed 2018.03.17).

Beier, G., Niehoff, S., Xue, B., 2018. More sustainability in industry through industrial internet of things? Appl. Sci. 8, 219. https://doi.org/10.3390/app8020219.

Bennane, A., Yacout, S., 2012. LAD-CBM; new data processing tool for diagnosis and prognosis in condition-based maintenance. J. Intell. Manuf. 23, 265–275.

Berger, C., Hees, A., Braunreuther, S., Reinhart, G., 2016. Characterization of cyber-physical sensor systems. Procedia CIRP 41, 638–643. In: https://doi.org/10.1016/j.procir.2015.12.019.

Bevilacqua, M., Ciarapica, F.E., Diamantini, C., Potena, D., 2017. Big data analytics methodologies applied at energy management in industrial sector: a case study. Int. J. RF Technol. Res. Appl. 8, 105–122. https://doi.org/10.3233/RFT-171671.

Bhinge, R., Park, J., Law, K.H., Dornfeld, D.A., Helu, M., Rachuri, S., 2016. Toward a generalized energy prediction model for machine tools. J. Manuf. Sci. Eng. 139, 041013. https://doi.org/10.1115/1.4034933.

Boeing, 2017. Boeing Data Analytics to Support Management of Flydubai 737 MAX Fleet. http://boeing.mediaroom.com/news-releases-statements (accessed 2017.03.23).

Bohlouli, M., Holland, A., Fathi, M., 2011. Knowledge integration of collaborative product design using cloud computing infrastructure. In: IEEE International Conference on Electro Information Technology, pp. 1–8. https://doi.org/10.1109/EIT.2011.5978611.

Boone, C.A., Skipper, J.B., Hazen, B.T., 2017. A framework for investigating the role of big data in service parts management. J. Clean. Prod. 153, 687–691. https://doi.org/10.1016/j.jclepro.2016.09.201.

Borthakur, D., 2007. The hadoop distributed file system: architecture and design. Hadoop Proj. Website 11, 21.

Bouikni, N., Rivest, L., Desrochers, A., 2008. A multiple views management system for concurrent engineering and PLM. Concurr. Eng. Res. Appl. 16, 61–72. https://doi.org/10.1177/1063293X07084641.

Çaliş, B., Bulkan, S., 2015. A research survey: review of AI solution strategies of job shop scheduling problem. J. Intell. Manuf. 26, 961–973. https://doi.org/10.1007/s10845-013-0837-8.

Catalin, Boja, Adrian, Pocovnicu, Lorena, B., 2012. Distributed parallel architecture for "big data. Inf. Econ. J. 16, 116–227.

Chai, J., Liu, J.N.K., Ngai, E.W.T., 2013. Application of decision-making techniques in supplier selection: a systematic review of literature. Expert Syst. Appl. 40, 3872–3885. https://doi.org/10.1016/j.eswa.2012.12.040.

Chen, T., Xiao, R., 2015. Modeling design iteration in product design and development and its solution by a novel artificial bee colony algorithm. Comput. Intell. Neurosci. 2014, 240828. https://doi.org/10.1155/2014/240828.

Cheng, Y., Chen, K., Sun, H., Zhang, Y., Tao, F., 2018a. Data and knowledge mining with big data towards smart production. J. Ind. Inf. Integr. 9, 1–13. https://doi.org/10.1016/j.jii.2017.08.001.

Cheng, Y., Tao, F., Xu, L., Zhao, D., 2018b. Advanced manufacturing systems: supply–demand matching of manufacturing resource based on complex networks and Internet of Things. Enterp. Inf. Syst. 12, 780–797. https://doi.org/10.1080/17517575.2016.1183263.

Cheng, Y., Tao, F., Zhao, D., Zhang, L., 2017. Modeling of manufacturing service supply–demand matching hypernetwork in service-oriented manufacturing systems. Robot. Comput. Integr. Manuf. 45, 59–72. https://doi.org/10.1016/j.rcim.2016.05.007.

Chien, C.F., Chuang, S.C., 2014. A framework for root cause detection of sub-batch processing system for semiconductor manufacturing big data analytics. IEEE Trans. Semicond. Manuf. 27, 475–488. https://doi.org/10.1109/TSM.2014.2356555.

Chong, A.Y.L., Ch'ng, E., Liu, M.J., Li, B., 2017. Predicting consumer product demands via Big Data: the roles of online promotional marketing and online reviews. Int. J. Prod. Res. 55, 5142–5156. https://doi.org/10.1080/00207543.2015.1066519.

Choudhary, A.K., Harding, J.A., Tiwari, M.K., 2009. Data mining in manufacturing: a review based on the kind of knowledge. J. Intell. Manuf. 20, 501–521.

Choy, K.L., Ho, G.T.S., Lee, C.K.H., Lam, H.Y., Cheng, S.W.Y., Siu, P.K.Y., Pang, G.K.H., Tang, V., Lee, J.C.H., Tsang, Y.P., 2016. A recursive operations strategy model for managing sustainable chemical product development and production. Int. J. Prod. Econ. 181, 262–272. https://doi.org/10.1016/j.ijpe.2016.07.011.

Costa, C., Santos, M.Y., 2017. Big Data: state-of-the-art concepts, techniques, technologies, modeling approaches and research challenges. Int. J. Comput. Sci. 44, 285–301.

Cynthia, B., Becerra-Fernandez, I., Short, J., Ross, J., 2012. Finding value in the information explosion. MIT Sloan Manag. Rev. 53, 18.

Da Cunha, C., Agard, B., Kusiak, A., 2006. Data mining for improvement of product quality. Int. J. Prod. Res. 44, 4027–4041.

Daki, H., El Hannani, A., Aqqal, A., Haidine, A., Dahbi, A., 2017. Big Data management in smart grid: concepts, requirements and implementation. J. Big Data 4. https://doi.org/10.1186/s40537-017-0070-y.

Dat, L.Q., Truc Linh, D.T., Chou, S.Y., Yu, V.F., 2012. Optimizing reverse logistic costs for recycling end-of-life electrical and electronic products. Expert Syst. Appl. 39, 6380–6387. https://doi.org/10.1016/j.eswa.2011.12.031.

Davis, J., Edgar, T., Graybill, R., Korambath, P., Schott, B., Swink, D., Wang, J., Wetzel, J., 2015. Smart manufacturing. Annu. Rev. Chem. Biomol. Eng. 6, 141–160. https://doi.org/10.1146/annurev-chembioeng-061114-123255.

Davis, J., Edgar, T., Porter, J., Bernaden, J., Sarli, M., 2012. Smart manufacturing, manufacturing intelligence and demand-dynamic performance. Comput. Chem. Eng. 47, 145–156. https://doi.org/10.1016/j.compchemeng.2012.06.037.

De Oña, J., De Oña, R., Calvo, F.J., 2012. A classification tree approach to identify key factors of transit service quality. Expert Syst. Appl. 39, 11164–11171. https://doi.org/10.1016/j.eswa.2012.03.037.
Demetgul, M., Yildiz, K., Taskin, S., Tansel, I.N., Yazicioglu, O., 2014. Fault diagnosis on material handling system using feature selection and data mining techniques. Measurement 55, 15–24. https://doi.org/10.1016/j.measurement.2014.04.037.
Demirkan, H., Delen, D., 2013. Leveraging the capabilities of service-oriented decision support systems: putting analytics and big data in cloud. Decis. Support Syst. 55, 412–421.
Demirkan, H., Kauffman, R.J., Vayghan, J.A., Fill, H.-G., Karagiannis, D., Maglio, P.P., 2008. Service-oriented technology and management: perspectives on research and practice for the coming decade. Electron. Commer. Res. Appl. 7, 356–376. https://doi.org/10.1016/j.elerap.2008.07.002.
Dhawan, R., Singh, K., Tuteja, A., 2014. When Big Data Goes Lean. https://www.mckinsey.com/business-functions/operations/our-insights/when-big-data-goes-lean (accessed 2017.03.20).
Dombrowski, U., Schmidt, S., Schmidtchen, K., 2014. Analysis and integration of design for X approaches in lean design as basis for a lifecycle optimized product design. Procedia CIRP 15, 385–390. In: https://doi.org/10.1016/j.procir.2014.06.023.
Dubey, R., Gunasekaran, A., Childe, S.J., Wamba, S.F., Papadopoulos, T., 2016. The impact of big data on world-class sustainable manufacturing. Int. J. Adv. Manuf. Technol. 84, 631–645. https://doi.org/10.1007/s00170-015-7674-1.
Dutta, D., Bose, I., 2015. Managing a big data project: the case of ramco cements limited. Int. J. Prod. Econ. 165, 293–306.
Efendigil, T., Önüt, S., Kahraman, C., 2009. A decision support system for demand forecasting with artificial neural networks and neuro-fuzzy models: a comparative analysis. Expert Syst. Appl. 36, 6697–6707. https://doi.org/10.1016/j.eswa.2008.08.058.
EIU, 2011. Big Data - Harnessing a Game-changing Asset. http://www.sas.com/resources/asset/SAS_BigData_final.pdf (accessed 2017.04.02).
ElMaraghy, H.A., ElMaraghy, W.H., 2014. Variety, complexity and value creation. In: Enabling Manufacturing Competitiveness and Economic Sustainability. Springer, pp. 1–7.
Elsevier, 2015. Home/Journals/IFAC-PapersOnLine. https://www.journals.elsevier.com/ifac-papersonline (accessed 2018.03.29).
Elsevier, 2012. Home/Journals/Procedia CIRP. In: https://www.journals.elsevier.com/procedia-cirp (accessed 2018.03.29).
Evans, P.C., Annunziata, M., 2012. Industrial internet: pushing the boundaries of minds and machines. General Electric Reports.
Fahimnia, B., Tang, C.S., Davarzani, H., Sarkis, J., 2015. Quantitative models for managing supply chain risks: a review. Eur. J. Oper. Res. https://doi.org/10.1016/j.ejor.2015.04.034.
Fang, K., Jiang, Y., Song, M., 2016. Customer profitability forecasting using Big Data analytics: a case study of the insurance industry. Comput. Ind. Eng. 101, 554–564. https://doi.org/10.1016/j.cie.2016.09.011.
Ferreiro, S., Sierra, B., Irigoien, I., Gorritxategi, E., 2011. Data mining for quality control: burr detection in the drilling process. Comput. Ind. Eng. 60, 801–810. https://doi.org/10.1016/j.cie.2011.01.018.
Ferrer, G., Heath, S.K., Dew, N., 2011. An RFID application in large job shop remanufacturing operations. Int. J. Prod. Econ. 133, 612–621. https://doi.org/10.1016/j.ijpe.2011.05.006.
Frank Ohlhorst, 2013. Big Data Analytics. TDWI Best Pract, pp. 1–35 report, fourth Quart.
Fung, K.Y., Kwong, C.K., Siu, K.W.M., Yu, K.M., 2012. A multi-objective genetic algorithm approach to rule mining for affective product design. Expert Syst. Appl. 39, 7411–7419. https://doi.org/10.1016/j.eswa.2012.01.065.
Gandomi, A., Haider, M., 2015. Beyond the hype: big data concepts, methods, and analytics. Int. J. Inf. Manag. 35, 137–144. https://doi.org/10.1016/j.ijinfomgt.2014.10.007.
Gantz, J., Reinsel, D., Gantz, B.J., 2011. Extracting value from chaos. IDC iview 1142, 1–12.
Gao, J., Yao, Y., Zhu, V.C.Y., Sun, L., Lin, L., 2011. Service-oriented manufacturing: a new product pattern and manufacturing paradigm. J. Intell. Manuf. 22, 435–446. https://doi.org/10.1007/s10845-009-0301-y.
Garfield, E., 2007. The evolution of the science citation index. Int. Microbiol. 10, 65–69. https://doi.org/10.2436/20.1501.01.10.
Garg, A., Lam, J.S.L., Gao, L., 2015. Energy conservation in manufacturing operations: modelling the milling process by a new complexity-based evolutionary approach. J. Clean. Prod. 108, 34–45.
Ge, X., Jackson, J., 2014. The big data application strategy for cost reduction in automotive industry. SAE Int. J. Commer. Veh. 7, 2014-01-2410. https://doi.org/10.4271/2014-01-2410.
General Electric, 2014. The Case for an Industrial Big Data Platform: Laying the Groundwork for the New Industrial Age. https://gesoftware.com/Industrial Big Data Platform.pdf (accessed 2017.07.16).
Geng, X., Chu, X., Zhang, Z., 2012. An association rule mining and maintaining approach in dynamic database for aiding product-service system conceptual design. Int. J. Adv. Manuf. Technol. https://doi.org/10.1007/s00170-011-3787-3.
Gubbi, J., Buyya, R., Marusic, S., Palaniswami, M., 2013. Internet of Things (IoT): a vision, architectural elements, and future directions. Futur. Gener. Comput. Syst. 29, 1645–1660. https://doi.org/10.1016/j.future.2013.01.010.
Gunasekaran, A., Papadopoulos, T., Dubey, R., Wamba, S.F., Childe, S.J., Hazen, B., Akter, S., 2017. Big data and predictive analytics for supply chain and organizational performance. J. Bus. Res. 70, 308–317.
Guo, J., Ya, G., 2015. Optimal strategies for manufacturing/remanufacturing system with the consideration of recycled products. Comput. Ind. Eng. 89, 226–234.
Gururajapathy, S.S., Mokhlis, H., Illias, H.A. Bin, Awalin, L.J., 2017. Support vector classification and regression for fault location in distribution system using voltage sag profile. IEEJ Trans. Electr. Electron. Eng. 12, 519–526.
Hamdaqa, M., Tahvildari, L., 2012. Cloud computing uncovered: a research landscape. Adv. Comput. 86, 41–85.
Hazen, B.T., Boone, C.A., Ezell, J.D., Jones-Farmer, L.A., 2014. Data quality for data science, predictive analytics, and big data in supply chain management: an introduction to the problem and suggestions for research and applications. Int. J. Prod. Econ. 154, 72–80. https://doi.org/10.1016/j.ijpe.2014.04.018.
Hazen, B.T., Skipper, J.B., Ezell, J.D., Boone, C.A., 2016. Big Data and predictive analytics for supply chain sustainability: a theory-driven research agenda. Comput. Ind. Eng. 101, 592–598.
Helo, P., Suorsa, M., Hao, Y., Anussornnitisarn, P., 2014. Toward a cloud-based manufacturing execution system for distributed manufacturing. Comput. Ind. 65, 646–656.
Hermann, M., Pentek, T., Otto, B., 2016. Design principles for industrie 4.0 scenarios. In: Proceedings of the Annual Hawaii International Conference on System Sciences, pp. 3928–3937. https://doi.org/10.1109/HICSS.2016.488.
Herterich, M.M., Uebernickel, F., Brenner, W., 2015. The impact of cyber-physical systems on industrial services in manufacturing. Procedia CIRP 30, 323–328.
Hofmann, E., 2017. Big data and supply chain decisions: the impact of volume, variety and velocity properties on the bullwhip effect. Int. J. Prod. Res. 55, 5108–5126. https://doi.org/10.1080/00207543.2015.1061222.
Holweg, M., 2007. The genealogy of lean production. J. Oper. Manag. 25, 420–437. https://doi.org/10.1016/j.jom.2006.04.001.
Hong, G., Xue, D., Tu, Y., 2010. Rapid identification of the optimal product configuration and its parameters based on customer-centric product modeling for one-of-a-kind production. Comput. Ind. 61, 270–279.
Hou, G., Sun, H., Jiang, Z., Pan, Z., Wang, Y., Zhang, X., Zhao, Y., Yao, Q., 2016. Life cycle assessment of grid-connected photovoltaic power generation from crystalline silicon solar modules in China. Appl. Energy 164, 882–890. https://doi.org/10.1016/j.apenergy.2015.11.023.
Hsieh, K.L., 2011. Employing a recommendation expert system based on mental accounting and artificial neural networks into mining business intelligence for study abroad's P/S recommendations. Expert Syst. Appl. 38, 14376–14381. https://doi.org/10.1016/j.eswa.2011.03.078.
Hu, H., Wen, Y., Chua, T.S., Li, X., 2014. Toward scalable systems for big data analytics: a technology tutorial. IEEE Access 2, 652–687. https://doi.org/0.11 09/ACCESS.2014.2332453.
Hu, L., Peng, T., Peng, C., Tang, R., 2017. Energy consumption monitoring for the order fulfilment in a ubiquitous manufacturing environment. Int. J. Adv. Manuf. Technol. 89, 3087–3100. https://doi.org/10.1007/s00170-016-9272-2.
Huang, C.F., Hsueh, S.L., 2010. Customer behavior and decision making in the refurbishment industry-a data mining approach. J. Civ. Eng. Manag. 16, 75–84. https://doi.org/10.3846/jcem.2010.07.
Huson, M., Nanda, D., 1995. The impact of just-in-time manufacturing on firm performance in the US. J. Oper. Manag. 12, 297–310. https://doi.org/10.1016/0272-6963(95)00011-G.
Ilsen, R., Meissner, H., Aurich, J.C., 2017. Optimizing energy consumption in a decentralized manufacturing system. J. Comput. Inf. Sci. Eng. 17, 021006. https://doi.org/10.1115/1.4034585.
Iqbal, M.H., Soomro, T.R., 2015. Big data analysis: Apache storm perspective. Int. J. Comput. Trends Technol. 9–14.
Jacobson, Z., Santhanam, N., 2016. Improving Semiconductor R & D. https://www.mckinsey.com/industries/semiconductors/our-insights/improving-semiconductor-r-and-d (accessed 2018.03.17).
Jacques, B., Eric, H., Sree, R., Michael, C., Tera, A., Peter, D., Nicolaus, H., Monica, T., 2017. How Artificial Intelligence Can Deliver Real Value to Companies. http://www.mckinsey.com/business-functions/mckinsey-analytics/our-insights/how-artificial-intelligence-can-deliver-real-value-to-companies. https://doi.org/10.1016/S1353-4858(17)30039-9 (accessed 2017.07.17).
Jagadish, H.V., Gehrke, J., Labrinidis, A., Papakonstantinou, Y., Patel, J.M., Ramakrishnan, R., Shahabi, C., 2014. Big data and its technical challenges. Commun. ACM 57, 86–94. https://doi.org/10.1145/2611567.
Jayal, A.D., Badurdeen, F., Dillon, O.W., Jawahir, I.S., 2010. Sustainable manufacturing: modeling and optimization challenges at the product, process and system levels. CIRP J. Manuf. Sci. Technol. 2, 144–152. https://doi.org/10.1016/j.cirpj.2010.03.006.
Jensen, J.P., Remmen, A., 2017. Enabling circular economy through product stewardship. Procedia Manuf. 8, 377–384. https://doi.org/10.1016/j.promfg.2017.02.048.
Jeschke, S., Brecher, C., Song, H., Rawat, D.B., 2017. Industrial internet of things. Int. J. Adv. Sci. Res. Eng. https://doi.org/10.7324/IJASRE.2017.32538.
Ji, W., Wang, L., 2017. Big data analytics based fault prediction for shop floor scheduling. J. Manuf. Syst. 43, 187–194. https://doi.org/10.1016/j.jmsy.2017.03.008.
Jia, F., Lei, Y., Lin, J., Zhou, X., Lu, N., 2016. Deep neural networks: a promising tool for fault characteristic mining and intelligent diagnosis of rotating machinery with massive data. Mech. Syst. Signal Process. 72 (73), 303–315. https://doi.org/10.1016/j.ymssp.2015.10.025.
Jiao, J., Zhang, Y., 2005. Product portfolio identification based on association rule mining. Comput. Des. 37, 149–172.

Jin, J., Liu, Y., Ji, P., Liu, H., 2016. Understanding big consumer opinion data for market-driven product design. Int. J. Prod. Res. 54, 3019–3041.
Jones-Farmer, L.A., Ezell, J.D., Hazen, B.T., 2014. Applying control chart methods to enhance data quality. Technometrics 56, 29–41.
Jun, H.-B., Shin, J.-H., Kiritsis, D., Xirouchakis, P., 2007. System architecture for closed-loop PLM. Int. J. Comput. Integr. Manuf. 20, 684–698. https://doi.org/10.1080/09511920701566624.
Jun, S.-P., Park, D.-H., Yeom, J., 2014. The possibility of using search traffic information to explore consumer product attitudes and forecast consumer preference. Technol. Forecast. Soc. Change 86, 237–253.
Jun, H.-B., Shin, J.-H., Kim, Y.-S., Kiritsis, D., Xirouchakis, P., 2009. A framework for RFID applications in product lifecycle management. Int. J. Comput. Integr. Manuf. 22, 595–615. https://doi.org/10.1080/09511920701501753.
Kagermann, H., Wahlster, W., Helbig, J., 2013. Recommendations for Implementing the Strategic Initiative INDUSTRIE 4.0: Securing the Future of German Manufacturing Industry. Final report of the Industrie 4.0 Working Group. Forschungsunion. https://doi.org/10.13140/RG.2.1.1205.8966.
Kaleel Ahmed, A., Senthilkumar, C.B., Nallusamy, S., 2018. Study on environmental impact through analysis of big data for sustainable and green supply chain management. Int. J. Mech. Prod. Eng. Res. Dev. 8, 1245–1254.
Kang, H.S., Lee, J.Y., Choi, S., Kim, H., Park, J.H., Son, J.Y., Kim, B.H., Noh, S. Do, 2016. Smart manufacturing: past research, present findings, and future directions. Int. J. Precis. Eng. Manuf. Green Technol. 3, 111–128. https://doi.org/10.1007/s40684-016-0015-5.
Kareem, B., Adekiigbe, A., 2017. Development of a system model for determining optimal personnel interaction strategy in a production industry. J. Eng. Res. 14, 49–63.
Kargari, M., Sepehri, M.M., 2012. Stores clustering using a data mining approach for distributing automotive spare-parts to reduce transportation costs. Expert Syst. Appl. 39, 4740–4748. https://doi.org/10.1016/j.eswa.2011.09.121.
Karimi-Majd, A.-M., Mahootchi, M., 2015. A new data mining methodology for generating new service ideas. Inf. Syst. E-bus. Manag. 13, 421–443.
Kelly, J., 2013. The Industrial Internet and Big Data Analytics: Opportunities and Challenges. http://wikibon.org/wiki/v/The Industrial Internet and Big Data Analytics%3A Opportunities and Challenges (accessed 2017.07.16).
Kim, Y., Chen, Y.S., Linderman, K., 2015. Supply network disruption and resilience: a network structural perspective. J. Oper. Manag. 33, 43–59.
Koetsier, J., 2014. Hadoop Founder Says Future of Big Data Looks like, Well, Hadoop: VB Insight. http://venturebeat.com/2014/04/10/hadoop-founder-says-future-ofbig-data-looks-like-well-hadoop/ (accessed 2017.04.04).
Köksal, G., Batmaz, İ., Testik, M.C., 2011. A review of data mining applications for quality improvement in manufacturing industry. Expert Syst. Appl. 38, 13448–13467.
Koonce, D.A., Tsai, S.C., 2000. Using data mining to find patterns in genetic algorithm solutions to a job shop schedule. Comput. Ind. Eng. 38, 361–374. https://doi.org/10.1016/S0360-8352(00)00050-4.
Kumar, A., Shankar, R., Choudhary, A., Thakur, L.S., 2016. A big data MapReduce framework for fault diagnosis in cloud-based manufacturing. Int. J. Prod. Res. 54, 7060–7073.
Kumar, A., Shankar, R., Thakur, L.S., 2018. A big data driven sustainable manufacturing framework for condition-based maintenance prediction. J. Comput. Sci. 27, 428–439. https://doi.org/10.1016/j.jocs.2017.06.006.
Kumru, M., Kumru, P.Y., 2014. Using artificial neural networks to forecast operation times in metal industry. Int. J. Comput. Integr. Manuf. 27, 48–59. https://doi.org/10.1080/0951192X.2013.800231.
Kurilova-Palisaitiene, J., Lindkvist, L., Sundin, E., 2015. Towards facilitating circular product life-cycle information flow via remanufacturing. Procedia CIRP 29, 780–785.
Kusiak, A., 2017. Smart manufacturing must embrace big data. Nature 544, 23–25.
Kusiak, A., Smith, M., 2007. Data mining in design of products and production systems. Annu. Rev. Contr. 31, 147–156.
Kusiak, A., Verma, A., 2012. Analyzing bearing faults in wind turbines: a data-mining approach. Renew. Energy 48, 110–116. https://doi.org/10.1016/j.renene.2012.04.020.
Kutschenreiter-Praszkiewicz, I., 2013. Application of neural network in QFD matrix. J. Intell. Manuf. 24, 397–404. https://doi.org/10.1007/s10845-011-0604-7.
Kwong, C.K., Jiang, H., Luo, X.G., 2016. AI-based methodology of integrating affective design, engineering, and marketing for defining design specifications of new products. Eng. Appl. Artif. Intell. 47, 49–60.
Laalaoui, Y., Bouguila, N., 2014. Pre-run-time scheduling in real-time systems: current researches and Artificial Intelligence perspectives. Expert Syst. Appl. 41, 2196–2210. https://doi.org/10.1016/j.eswa.2013.09.018.
Lam, K.C., Oshodi, O.S., 2016. Using univariate models for construction output forecasting: comparing artificial intelligence and econometric techniques. J. Manag. Eng. 32, 04016021. https://doi.org/10.1061/(ASCE)ME.1943-5479.0000462.
Lamba, K., Singh, S.P., 2017. Big data in operations and supply chain management: current trends and future perspectives. Prod. Plann. Contr. 28, 877–890. https://doi.org/10.1080/09537287.2017.1336787.
Laney, D., 2001. 3-D data management:controlling data volume, velocity and variety. META Gr. Res. Note 1–4.
Lee, C.K.M., Ho, W., Ho, G.T.S., Lau, H.C.W., 2011. Design and development of logistics workflow systems for demand management with RFID. Expert Syst. Appl. 38, 5428–5437. https://doi.org/10.1016/j.eswa.2010.10.012.
Lee, H., Ryu, K., Cho, Y., 2017. A framework of a smart injection molding system based on real-time data. Procedia Manuf. 11, 1004–1011. https://doi.org/10.1016/j.promfg.2017.07.206.
Lee, I., 2007. Evaluating artificial intelligence heuristics for a flexible Kanban system: simultaneous Kanban controlling and scheduling. Int. J. Prod. Res. 45, 2859–2873. https://doi.org/10.1080/00207540600806505.
Lee, J., Ardakani, H.D., Yang, S., Bagheri, B., 2015a. Industrial big data analytics and cyber-physical systems for future maintenance & service innovation. Procedia CIRP 38, 3–7.
Lee, J., Bagheri, B., Kao, H.-A., 2015b. A cyber-physical systems architecture for industry 4.0-based manufacturing systems. Manuf. Lett. 3, 18–23.
Lee, J., Kao, H.A., Yang, S., 2014. Service innovation and smart analytics for Industry 4.0 and big data environment. Procedia CIRP 16, 3–8. In: https://doi.org/10.1016/j.procir.2014.02.001.
Lee, J., Lapira, E., Bagheri, B., Kao, H. an, 2013. Recent advances and trends in predictive manufacturing systems in big data environment. Manuf. Lett. 1, 38–41. https://doi.org/10.1016/j.mfglet.2013.09.005.
Lei, N., Moon, S.K., 2015. A Decision Support System for market-driven product positioning and design. Decis. Support Syst. 69, 82–91. https://doi.org/10.1016/j.dss.2014.11.010.
Lei, Y., Jia, F., Lin, J., Xing, S., Ding, S.X., 2016. An intelligent fault diagnosis method using unsupervised feature learning towards mechanical big data. IEEE Trans. Ind. Electron. 63, 3137–3147. https://doi.org/10.1109/TIE.2016.2519325.
Leitão, P., Colombo, A.W., Karnouskos, S., 2016. Industrial automation based on cyber-physical systems technologies: prototype implementations and challenges. Comput. Ind. 81, 11–25. https://doi.org/10.1016/j.compind.2015.08.004.
Li, B., Ch'ng, E., Chong, A.Y.L., Bao, H., 2016a. Predicting online e-marketplace sales performances: a big data approach. Comput. Ind. Eng. 101, 565–571. https://doi.org/10.1016/j.cie.2016.08.009.
Li, C., Sanchez, R.-V., Zurita, G., Cerrada, M., Cabrera, D., Vásquez, R.E., 2015a. Multimodal deep support vector classification with homologous features and its application to gearbox fault diagnosis. Neurocomputing 168, 119–127. https://doi.org/10.1016/j.neucom.2015.06.008.
Li, D., Tang, H., Wang, S., Liu, C., 2017a. A big data enabled load-balancing control for smart manufacturing of Industry 4.0. Cluster Comput. 20, 1855–1864. https://doi.org/10.1007/s10586-017-0852-1.
Li, H., Parikh, D., He, Q., Qian, B., Li, Z., Fang, D., Hampapur, A., 2014. Improving rail network velocity: a machine learning approach to predictive maintenance. Transp. Res. Part C Emerg. Technol. 45, 17–26. https://doi.org/10.1016/j.trc.2014.04.013.
Li, H., Wu, D., Li, G.X., Ke, Y.H., Liu, W.J., Zheng, Y.H., Lin, X. La, 2015b. Enhancing telco service quality with big data enabled churn analysis: infrastructure, model, and deployment. J. Comput. Sci. Technol. 30, 1201–1214. https://doi.org/10.1007/s11390-015-1594-2.
Li, J., Tao, F., Cheng, Y., Zhao, L., 2015c. Big Data in product lifecycle management. Int. J. Adv. Manuf. Technol. 81, 667–684. https://doi.org/10.1007/s00170-015-7151-x.
Li, J., Zhang, Y., Du, D., Liu, Z., 2017b. Improvements in the decision making for Cleaner Production by data mining: case study of vanadium extraction industry using weak acid leaching process. J. Clean. Prod. 143, 582–597. https://doi.org/10.1016/j.jclepro.2016.12.071.
Li, J.Q., Yu, F.R., Deng, G., Luo, C., Ming, Z., Yan, Q., 2017c. Industrial internet: a survey on the enabling technologies, applications, and challenges. IEEE Commun. Surv. Tutorials 19, 1504–1526. https://doi.org/10.1109/COMST.2017.2691349.
Li, S., Nahar, K., Fung, B.C.M., 2013. Product customization of tablet computers based on the information of online reviews by customers. J. Intell. Manuf. 26, 97–110. https://doi.org/10.1007/s10845-013-0765-7.
Li, X., Song, J., Huang, B., 2016b. A scientific workflow management system architecture and its scheduling based on cloud service platform for manufacturing big data analytics. Int. J. Adv. Manuf. Technol. 84, 119–131. https://doi.org/10.1007/s00170-015-7804-9.
Li, Y., Sun, Z., Han, L., Mei, N., 2017d. Fuzzy comprehensive evaluation method for energy management systems based on an internet of things. IEEE Access 5, 21312–21322. https://doi.org/10.1109/ACCESS.2017.2728081.
Li, Y., Tao, F., Cheng, Y., Zhang, X., Nee, A.Y.C., 2017e. Complex networks in advanced manufacturing systems. J. Manuf. Syst. 43, 409–421. https://doi.org/10.1016/j.jmsy.2016.12.001.
Liang, Y.C., Lu, X., Li, W.D., Wang, S., 2018. Cyber Physical System and Big Data enabled energy efficient machining optimisation. J. Clean. Prod. 187, 46–62. https://doi.org/10.1016/j.jclepro.2018.03.149.
Liao, Y., Lezoche, M., Panetto, H., Boudjlida, N., Loures, E.R., 2015. Semantic annotation for knowledge explicitation in a product lifecycle management context: a survey. Comput. Ind. 71, 24–34. https://doi.org/10.1016/j.compind.2015.03.005.
Lieber, D., Stolpe, M., Konrad, B., Deuse, J., Morik, K., 2013. Quality prediction in interlinked manufacturing processes based on supervised & unsupervised machine learning. In: Procedia CIRP, pp. 193–198. In: https://doi.org/10.1016/j.procir.2013.05.033.
Liou, J.J.H., Tang, C.H., Yeh, W.C., Tsai, C.Y., 2011. A decision rules approach for improvement of airport service quality. Expert Syst. Appl. 38, 13723–13730. https://doi.org/10.1016/j.eswa.2011.04.168.
Liu, J., Xu, W., Zhang, J., Zhou, Z., Pham, D.T., 2016. Industrial cloud robotics towards sustainable manufacturing. In: Materials; Biomanufacturing; Properties, Applications and Systems; Sustainable Manufacturing, vol. 2 p. V002T04A017. https://doi.org/10.1115/MSEC2016-8733.
Liu, Y., 2013. Sustainable competitive advantage in turbulent business environments. Int. J. Prod. Res. 51, 2821–2841. https://doi.org/10.1080/00207543.2012.

720392.
Liu, Y., Jin, J., Ji, P., Harding, J.A., Fung, R.Y.K., 2013. Identifying helpful online reviews: a product designer's perspective. Comput. Des. 45, 180–194.
Liu, Y., Liang, L., 2015. Evaluating and developing resource-based operations strategy for competitive advantage: an exploratory study of Finnish high-tech manufacturing industries. Int. J. Prod. Res. 53, 1019–1037. https://doi.org/10.1080/00207543.2014.932936.
Louhghalam, A., Akbarian, M., Ulm, F.-J., 2017. Carbon management of infrastructure performance: integrated big data analytics and pavement-vehicle-interactions. J. Clean. Prod. 142, 956–964. https://doi.org/10.1016/j.jclepro.2016.06.198.
Lu, Q., Li, S., Zhang, W., 2016. Genetic Algorithm Based Job Scheduling for Big Data Analytics. 2015 Int. Conf. Identification, Information, Knowl. Internet Things (IIKI 2015) 2016, pp. 33–38. https://doi.org/10.1109/IIKI.2015.14.
Luo, H., Du, B., Huang, G.Q., Chen, H., Li, X., 2013. Hybrid flow shop scheduling considering machine electricity consumption cost. Int. J. Prod. Econ. 146, 423–439. https://doi.org/10.1016/j.ijpe.2013.01.028.
Luttropp, C., Johansson, J., 2010. Improved recycling with life cycle information tagged to the product. J. Clean. Prod. 18, 346–354. https://doi.org/10.1016/j.jclepro.2009.10.023.
Ma, J., Kwak, M., Kim, H.M., 2014. Demand trend mining for predictive life cycle design. J. Clean. Prod. 68, 189–199. https://doi.org/10.1016/j.jclepro.2014.01.026.
Madenas, N., Tiwari, A., Turner, C.J., Woodward, J., 2014. Information flow in supply chain management: a review across the product lifecycle. CIRP J. Manuf. Sci. Technol. 7, 335–346. https://doi.org/10.1016/j.cirpj.2014.07.002.
Magro, M.C., Pinceti, P., 2009. A confirmation technique for predictive maintenance using the Rough Set Theory. Comput. Ind. Eng. 56, 1319–1327. https://doi.org/10.1016/j.cie.2008.07.024.
Mahdavi, I., Shirazi, B., Ghorbani, N., Sahebjamnia, N., 2013. IMAQCS: design and implementation of an intelligent multi-agent system for monitoring and controlling quality of cement production processes. Comput. Ind. 64, 290–298. https://doi.org/10.1016/j.compind.2012.11.005.
Manyika, J., Chui, M., Brown, B., Bughin, J., Dobbs, R., Roxburgh, C., Byers, A.H., 2011. Big Data: the Next Frontier for Innovation, Competition, and Productivity. McKinsey Global Institute. http://www.mckinsey.com/business-functions/digital-mckinsey/our-insights/big-data-the-next-frontier-for-innovation (accessed 2017.03.11).
Martillano, D.A., Dita, J.M.R., Cruz, C.G., Sadhra, K.S., 2017. Android based real-time industrial emission monitoring system using IoT technology. J. Commun. 12, 623–629. https://doi.org/10.12720/jcm.12.11.623-629.
Marwah, M., Shah, A., Bash, C., Patel, C., Ramakrishnan, N., 2011. Using data mining to help design sustainable products. IEEE Comput. 44, 103–106.
Mashhadi, A.R., Behdad, S., 2017. Optimal sorting policies in remanufacturing systems: application of product life-cycle data in quality grading and end-of-use recovery. J. Manuf. Syst. 43, 15–24.
Mashhadi, A.R., Esmaeilian, B., Cade, W., Wiens, K., Behdad, S., 2016. Mining consumer experiences of repairing electronics: product design insights and business lessons learned. J. Clean. Prod. 137, 716–727.
Mashingaidze, K., Backhouse, J., 2017. The relationships between definitions of big data, business intelligence and business analytics: a literature review. Int. J. Bus. Inf. Syst. 26, 488–505. https://doi.org/10.1504/IJBIS.2017.087749.
McKinsey & Company, 2017. Ask the AI Experts: What's Driving Today's Progress in AI? http://www.mckinsey.com/business-functions/mckinsey-analytics/our-insights/ask-the-ai-experts-whats-driving-todays-progress-in-ai (accessed 2017.07.17).
Mehrsai, A., Karimi, H.-R., Thoben, K.-D., Scholz-Reiter, B., 2013. Application of learning pallets for real-time scheduling by the use of radial basis function network. Neurocomputing 101, 82–93.
Mell, P., Grance, T., 2009. Perspectives on Cloud Computing and Standards. NIST, USA.
Miranda, J., Pérez-Rodríguez, R., Borja, V., Wright, P.K., Molina, A., 2017. Integrated product, process and manufacturing system development reference model to develop cyber-physical production systems - the sensing, smart and sustainable microfactory case study. IFAC-PapersOnLine 50, 13065–13071. https://doi.org/10.1016/j.ifacol.2017.08.2006.
Mittal, S., Khan, M.A., Wuest, T., 2016. Smart manufacturing: characteristics and technologies. In: IFIP International Conference on Product Lifecycle Management, pp. 539–548.
Moharana, U.C., Sarmah, S.P., 2016. Determination of optimal order-up to level quantities for dependent spare parts using data mining. Comput. Ind. Eng. 95, 27–40. https://doi.org/10.1016/j.cie.2016.01.024.
Monostori, L., 2014. Cyber-physical production systems: roots, expectations and R&D challenges. Procedia CIRP 17, 9–13. In: https://doi.org/10.1016/j.procir.2014.03.115.
Moreno, M.V., Dufour, L., Skarmeta, A.F., Jara, A.J., Genoud, D., Ladevie, B., Bezian, J.-J., 2016. Big data: the key to energy efficiency in smart buildings. Soft Comput. 20, 1749–1762.
Nadakatti, M., Ramachandra, A., Santosh, A.N.K., 2008. Artificial intelligence-based condition monitoring for plant maintenance. Assemb. Autom. 28, 143–150. https://doi.org/10.1108/01445150810863725.
Nagorny, K., Lima-Monteiro, P., Barata, J., Colombo, A.W., 2017. Big data analysis in smart manufacturing: a review. Int. J. Commun. Netw. Syst. Sci. 10, 31–58. https://doi.org/10.4236/ijcns.2017.103003.
Ness, D., Swift, J., Ranasinghe, D.C., Xing, K., Soebarto, V., 2015. Smart steel: new paradigms for the reuse of steel enabled by digital tracking and modelling. J. Clean. Prod. 98, 292–303. https://doi.org/10.1016/j.jclepro.2014.08.055.
Ngu, A.H., Gutierrez, M., Metsis, V., Nepal, S., Sheng, Q.Z., 2017. IoT middleware: a survey on issues and enabling technologies. IEEE Internet Things J. 4, 1–20. https://doi.org/10.1109/JIOT.2016.2615180.
NIST, 2012. NIST Big Data Program. https://bigdatawg.nist.gov/home.php (accessed 2017.04.16).
Niu, B., Zou, Z., 2017. Better demand signal, better decisions? Evaluation of big data in a licensed remanufacturing supply chain with environmental risk considerations. Risk Anal. 37, 1550–1565. https://doi.org/10.1111/risa.12796.
Nyanteh, Y.D., Srivastava, S.K., Edrington, C.S., Cartes, D.A., 2013. Application of artificial intelligence to stator winding fault diagnosis in Permanent Magnet Synchronous Machines. Elec. Power Syst. Res. 103, 201–213. https://doi.org/10.1016/j.epsr.2013.05.018.
Onanena, R., Oukhellou, L., Candusso, D., Same, A., Hissel, D., Aknin, P., 2010. Estimation of fuel cell operating time for predictive maintenance strategies. Int. J. Hydrogen Energy 35, 8022–8029. https://doi.org/10.1016/j.ijhydene.2010.05.039.
Opresnik, D., Taisch, M., 2015. The value of big data in servitization. Int. J. Prod. Econ. 165, 174–184. https://doi.org/10.1016/j.ijpe.2014.12.036.
Orji, I.J., Wei, S., 2015. An innovative integration of fuzzy-logic and systems dynamics in sustainable supplier selection: a case on manufacturing industry. Comput. Ind. Eng. 88, 1–12. https://doi.org/10.1016/j.cie.2015.06.019.
Oses, N., Legarretaetxebarria, A., Quartulli, M., GarcÃ-a, I., Serrano, M., 2016. Uncertainty reduction in measuring and verification of energy savings by statistical learning in manufacturing environments. Int. J. Interact. Des. Manuf. 10, 291–299. https://doi.org/10.1007/s12008-016-0302-y.
Palensky, P., Widl, E., Elsheikh, A., 2014. Simulating cyber-physical energy systems: challenges, tools and methods. IEEE Trans. Syst. Man, Cybern. Syst. 44, 318–326. https://doi.org/10.1109/TSMCC.2013.2265739.
Pang, J., 2015. Early warning system for complex products quality improvement using data mining and neural network. Metall. Min. Ind. 7, 377–385.
Papadopoulos, T., Gunasekaran, A., Dubey, R., Altay, N., Childe, S.J., Fosso-Wamba, S., 2017. The role of Big Data in explaining disaster resilience in supply chains for sustainability. J. Clean. Prod. 142, 1108–1118.
Peng, H.G., Wang, J.Q., 2017. Cloud decision model for selecting sustainable energy crop based on linguistic intuitionistic information. Int. J. Syst. Sci. 48, 3316–3333. https://doi.org/10.1080/00207721.2017.1367433.
Perera, C., Liu, C.H., Jayawardena, S., 2015. The emerging internet of things marketplace from an industrial perspective: a survey. IEEE Trans. Emerg. Top. Comput. 3, 585–598.
Petrochenkov, A.B., Bochkarev, S.V., Ovsyannikov, M.V., Bukhanov, S.A., 2015. Construction of an ontological model of the life cycle of electrotechnical equipment. Russ. Electr. Eng. 86, 320–325. https://doi.org/10.3103/S1068371215060115.
Purarjomandlangrudi, A., Ghapanchi, A.H., Esmalifalak, M., 2014. A data mining approach for fault diagnosis: an application of anomaly detection algorithm. Measurement 55, 343–352. https://doi.org/10.1016/j.measurement.2014.05.029.
Qin, Y., Zhao, L., Yao, Y., Xu, D., 2011. Multistage machining processes variation propagation analysis based on machining processes weighted network performance. Int. J. Adv. Manuf. Technol. 55, 487–499.
Raheja, D., Llinas, J., Nagi, R., Romanowski, C., 2006. Data fusion/data mining-based architecture for condition-based maintenance. Int. J. Prod. Res. 44, 2869–2887.
Rashid, M.M., Amar, M., Gondal, I., Kamruzzaman, J., 2016. A data mining approach for machine fault diagnosis based on associated frequency patterns. Appl. Intell. 45, 638–651.
Ren, S., Zhao, X., Huang, B., Wang, Z., Song, X., 2018. A framework for shopfloor material delivery based on real-time manufacturing big data. J. Ambient Intell. Humaniz. Comput. https://doi.org/10.1007/s12652-018-1017-7.
Renzi, C., Leali, F., Cavazzuti, M., Andrisano, A.O., 2014. A review on artificial intelligence applications to the optimal design of dedicated and reconfigurable manufacturing systems. Int. J. Adv. Manuf. Technol. 72, 403–418. https://doi.org/10.1007/s00170-014-5674-1.
Roh, S.B., Oh, S.K., 2016. Identification of plastic wastes by using fuzzy radial basis function neural networks classifier with conditional fuzzy C-means clustering. J. Electr. Eng. Technol. 11, 1872–1879. https://doi.org/10.5370/JEET.2016.11.6.1872.
Rowley, J., Slack, F., 2004. Conducting a literature review. Manag. Res. News 27, 31–39. https://doi.org/10.1108/01409170410784185.
Roy, V., Singh, S., 2017. Mapping the business focus in sustainable production and consumption literature: review and research framework. J. Clean. Prod. 150, 224–236. https://doi.org/10.1016/j.jclepro.2017.03.040.
Rusinko, C., 2007. Green manufacturing: an evaluation of environmentally sustainable manufacturing practices and their impact on competitive outcomes. IEEE Trans. Eng. Manag. 54, 445–454. https://doi.org/10.1109/TEM.2007.900806.
S2 Manufacturing International Conference, 2016. Home. http://s2m.fa.ulisboa.pt/ (accessed 2018.03.29).
Sakao, T., Shimomura, Y., 2007. Service Engineering: a novel engineering discipline for producers to increase value combining service and product. J. Clean. Prod. 15, 590–604. https://doi.org/10.1016/j.jclepro.2006.05.015.
Sanchez, L., Nagi, R., 2001. A review of agile manufacturing systems. Int. J. Prod. Res. 39, 3561–3600. https://doi.org/10.1080/00207540110068790.
Santos, J.P., Oliveira, M., Almeida, F.G., Pereira, J.P., Reis, A., 2011. Improving the environmental performance of machine-tools: influence of technology and throughput on the electrical energy consumption of a press-brake. J. Clean. Prod. 19, 356–364. https://doi.org/10.1016/j.jclepro.2010.10.009.

Shahzad, A., Mebarki, N., 2012. Data mining based job dispatching using hybrid simulation-optimization approach for shop scheduling problem. Eng. Appl. Artif. Intell. 25, 1173–1181. https://doi.org/10.1016/j.engappai.2012.04.001.
Shao, G., Brodsky, A., Shin, S.J., Kim, D.B., 2017. Decision guidance methodology for sustainable manufacturing using process analytics formalism. J. Intell. Manuf. 28, 455–472. https://doi.org/10.1007/s10845-014-0995-3.
Shin, S.J., Kim, D.B., Shao, G., Brodsky, A., Lechevalier, D., 2017. Developing a decision support system for improving sustainability performance of manufacturing processes. J. Intell. Manuf. 28, 1421–1440. https://doi.org/10.1007/s10845-015-1059-z.
Shin, S.J., Woo, J., Rachuri, S., 2014. Predictive analytics model for power consumption in manufacturing. Procedia CIRP 15, 153–158. https://doi.org/10.1016/j.procir.2014.06.036.
Shrouf, F., Miragliotta, G., 2015. Energy management based on Internet of Things: practices and framework for adoption in production management. J. Clean. Prod. 100, 235–246. https://doi.org/10.1016/j.jclepro.2015.03.055.
Sibalija, T.V., Petronic, S.Z., Majstorovic, V.D., Prokic-Cvetkovic, R., Milosavljevic, A., 2011. Multi-response design of Nd:YAG laser drilling of Ni-based superalloy sheets using Taguchi's quality loss function, multivariate statistical methods and artificial intelligence. Int. J. Adv. Manuf. Technol. 54, 537–552. https://doi.org/10.1007/s00170-010-2945-3.
Siemens, 2014. Big Data Pays Big in Power Plant Operation. http://www.energy.siemens.com/hq/en/energy-topics/energy-stories/rds-tahaddart.htm (accessed 2017.03.23).
Sim, H., Choi, D., Kim, C.O., 2014. A data mining approach to the causal analysis of product faults in multi-stage PCB manufacturing. Int. J. Precis. Eng. Manuf. 15, 1563–1573.
Simeone, A., Luo, Y., Woolley, E., Rahimifard, S., Boër, C., 2016. A decision support system for waste heat recovery in manufacturing. CIRP Ann. Manuf. Technol. 65, 21–24. https://doi.org/10.1016/j.cirp.2016.04.034.
Smith, S., Smith, G., Chen, W.H., 2012. Disassembly sequence structure graphs: an optimal approach for multiple-target selective disassembly sequence planning. Adv. Eng. Inf. 26, 306–316. https://doi.org/10.1016/j.aei.2011.11.003.
Song, M., Cen, L., Zheng, Z., Fisher, R., Liang, X., Wang, Y., Huisingh, D., 2017a. How would big data support societal development and environmental sustainability? Insights and practices. J. Clean. Prod. 142 (Part 2), 489–500. https://doi.org/10.1016/j.jclepro.2016.10.091.
Song, M., Du, Q., Zhu, Q., 2017b. A theoretical method of environmental performance evaluation in the context of big data. Prod. Plann. Contr. 28, 976–984. https://doi.org/10.1080/09537287.2017.1336801.
Song, M.L., Fisher, R., Wang, J.L., Cui, L.B., 2018. Environmental performance evaluation with big data: theories and methods. Ann. Oper. Res. 270, 459–472. https://doi.org/10.1007/s10479-016-2158-8.
Song, W., Sakao, T., 2017. A customization-oriented framework for design of sustainable product/service system. J. Clean. Prod. 140, 1672–1685.
Song, Z., Moon, Y., 2017. Assessing sustainability benefits of cyber manufacturing systems. Int. J. Adv. Manuf. Technol. 90, 1365–1382. https://doi.org/10.1007/s00170-016-9428-0.
Soroka, A., Liu, Y., Han, L., Haleem, M.S., 2017. Big data driven customer insights for SMEs in redistributed manufacturing. In: Procedia CIRP, pp. 692–697. In: https://doi.org/10.1016/j.procir.2017.03.319.
Stefanovic, N., 2015. Collaborative predictive business intelligence model for spare parts inventory replenishment. Comput. Sci. Inf. Syst. 12, 911–930. https://doi.org/10.2298/CSIS141101034S.
Stewart, R.E., 2006. Impact of myocardial perfusion scintigraphy in general cardiology practice. Cardiol. Rev. 23, 25–26. https://doi.org/10.1115/MSEC2016-8726.
Suganthi, L., Iniyan, S., Samuel, A.A., 2015. Applications of fuzzy logic in renewable energy systems - a review. Renew. Sustain. Energy Rev. 48, 585–607. https://doi.org/10.1016/j.rser.2015.04.037.
Sun, J., Xu, W., Ma, J., Sun, J., 2015. Leverage RAF to find domain experts on research social network services: a big data analytics methodology with MapReduce framework. Int. J. Prod. Econ. 165, 185–193. https://doi.org/10.1016/j.ijpe.2014.12.038.
Susto, G.A., Schirru, A., Pampuri, S., McLoone, S., Beghi, A., 2015. Machine learning for predictive maintenance: a multiple classifier approach. IEEE Trans. Ind. Inf. 11, 812–820. https://doi.org/10.1109/TII.2014.2349359.
Tan, K.H., Zhan, Y., Ji, G., Ye, F., Chang, C., 2015. Harvesting big data to enhance supply chain innovation capabilities: an analytic infrastructure based on deduction graph. Int. J. Prod. Econ. 165, 223–233. https://doi.org/10.1016/j.ijpe.2014.12.034.
Tankard, C., 2012. Big data security. Netw. Secur. 2012, 5–8. https://doi.org/10.1016/S1353-4858(12)70063-6.
Tao, F., Cheng, J., Cheng, Y., Gu, S., Zheng, T., Yang, H., 2017. SDMSim: a manufacturing service supply–demand matching simulator under cloud environment. Robot. Comput. Integr. Manuf. 45, 34–46. https://doi.org/10.1016/j.rcim.2016.07.001.
Tao, F., Cheng, J., Qi, Q., Zhang, M., Zhang, H., Sui, F., 2018. Digital twin-driven product design, manufacturing and service with big data. Int. J. Adv. Manuf. Technol. 94, 3563–3576. https://doi.org/10.1007/s00170-017-0233-1.
Tao, F., Cheng, Y., Xu, L. Da, Zhang, L., Li, B.H., 2014a. CCIoT-CMfg: cloud computing and internet of things-based cloud manufacturing service system. IEEE Trans. Ind. Inf. 10, 1435–1442. https://doi.org/10.1109/TII.2014.2306383.
Tao, F., Wang, Y., Zuo, Y., Yang, H., Zhang, M., 2016. Internet of Things in product life-cycle energy management. J. Ind. Inf. Integr. 1, 26–39. https://doi.org/10.1016/j.jii.2016.03.001.
Tao, F., Zhang, L., Liu, Y., Cheng, Y., Wang, L., Xu, X., 2015. Manufacturing service management in cloud manufacturing: overview and future research directions. J. Manuf. Sci. Eng. 137, 040912. https://doi.org/10.1115/1.4030510.
Tao, F., Zuo, Y., Xu, L. Da, Lv, L., Zhang, L., 2014b. Internet of things and BOM-Based life cycle assessment of energy-saving and emission-reduction of products. IEEE Trans. Ind. Inf. 10, 1252–1261. https://doi.org/10.1109/TII.2014.2306771.
TechTarget, 2012. Big Data Analytics. http://searchbusinessanalytics.techtarget.com/resources/Big-data-analytics (accessed 2017.07.17).
Telukdarie, A., Haung, Y., others, 2006. A case study on artificial intelligence based cleaner production evaluation system for surface treatment facilities. J. Clean. Prod. 14, 1622–1634.
Thoben, K.-D., Wiesner, S., Wuest, T., 2017. "Industrie 4.0" and smart manufacturing – a review of research issues and application examples. Int. J. Autom. Technol. 11, 4–19. https://doi.org/10.20965/ijat.2017.p0004.
Thürer, M., Tomašević, I., Stevenson, M., Qu, T., Huisingh, D., 2018. A systematic review of the literature on integrating sustainability into engineering curricula. J. Clean. Prod. 181, 608–617. https://doi.org/10.1016/j.jclepro.2017.12.130.
Ting, S.L., Tse, Y.K., Ho, G.T.S., Chung, S.H., Pang, G., 2014. Mining logistics data to assure the quality in a sustainable food supply chain: a case in the red wine industry. Int. J. Prod. Econ. 152, 200–209. https://doi.org/10.1016/j.ijpe.2013.12.010.
Tranfield, D., Denyer, D., Smart, P., 2003. Towards a methodology for developing evidence: informed management knowledge by means of systematic review. Br. J. Manag. 14, 207–222. https://doi.org/10.1111/1467-8551.00375.
Tsafarakis, S., Saridakis, C., Baltas, G., Matsatsinis, N., 2013. Hybrid particle swarm optimization with mutation for optimizing industrial product lines: an application to a mixed solution space considering both discrete and continuous design variables. Ind. Market. Manag. 42, 496–506. https://doi.org/10.1016/j.indmarman.2013.03.002.
Tukker, A., 2015. Product services for a resource-efficient and circular economy - a review. J. Clean. Prod. 97, 76–91. https://doi.org/10.1016/j.jclepro.2013.11.049.
Unal, M., Sahin, Y., Onat, M., Demetgul, M., Kucuk, H., 2016. Fault diagnosis of rolling bearings using data mining techniques and boosting. J. Dyn. Syst. Meas. Contr. 139, 021003. https://doi.org/10.1115/1.4034604.
Valilai, O.F., Houshmand, M., 2013. A collaborative and integrated platform to support distributed manufacturing system using a service-oriented approach based on cloud computing paradigm. Robot. Comput. Integr. Manuf. 29, 110–127.
Veldman, J., Gaalman, G., 2014. A model of strategic product quality and process improvement incentives. Int. J. Prod. Econ. 149, 202–210.
Vidal, T., Crainic, T.G., Gendreau, M., Prins, C., 2012. Heuristics for multi-attribute vehicle routing problems: a survey and synthesis. Eur. J. Oper. Res. 231, 1–21.
Vikhorev, K., Greenough, R., Brown, N., 2013. An advanced energy management framework to promote energy awareness. J. Clean. Prod. 43, 103–112.
Waibel, M.W., Steenkamp, L.P., Moloko, N., Oosthuizen, G.A., 2017. Investigating the effects of smart production systems on sustainability elements. Procedia Manuf. 8, 731–737. https://doi.org/10.1016/j.promfg.2017.02.094.
Wamba, S.F., 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.
Wang, C.H., 2015a. Using the theory of inventive problem solving to brainstorm innovative ideas for assessing varieties of phone-cameras. Comput. Ind. Eng. 85, 227–234. https://doi.org/10.1016/j.cie.2015.04.003.
Wang, Y., Zhang, L., 2017. A combined fault diagnosis method for power transformer in big data environment. Math. Probl Eng. 2017. https://doi.org/10.1155/2017/9670290.
Wang, J., Zhang, Y., Liu, Y., Wu, N., 2018a. Multi-agent and bargaining-game-based real-time scheduling for internet of things-enabled flexible job shop. IEEE Internet Things J. https://doi.org/10.1109/JIOT.2018.2871346.
Wang, K., Wang, Y., Sun, Y., Guo, S., Wu, J., 2016a. Green industrial Internet of Things architecture: an energy-efficient perspective. IEEE Commun. Mag. 54, 48–54.
Wang, L., 2015b. Collaborative robot monitoring and control for enhanced sustainability. Int. J. Adv. Manuf. Technol. 81, 1433–1445. https://doi.org/10.1007/s00170-013-4864-6.
Wang, L., Wang, X.V., Gao, L., Váncza, J., 2014. A cloud-based approach for WEEE remanufacturing. CIRP Ann. - Manuf. Technol. 63, 409–412. https://doi.org/10.1016/j.cirp.2014.03.114.
Wang, W., Yang, H., Zhang, Y., Xu, J., 2018b. IoT-enabled real-time energy efficiency optimisation method for energy-intensive manufacturing enterprises. Int. J. Comput. Integr. Manuf. 31, 362–379. https://doi.org/10.1080/0951192X.2017.1337929.
Wang, X.V., Wang, L., 2014. From cloud manufacturing to cloud remanufacturing: a cloud-based approach for WEEE recovery. Manuf. Lett. 2, 91–95.
Wang, Y., Shao, Y., Matovic, M.D., Whalen, J.K., 2016b. Recycling combustion ash for sustainable cement production: a critical review with data-mining and time-series predictive models. Constr. Build. Mater. 123, 673–689. https://doi.org/10.1016/j.conbuildmat.2016.07.031.
Wang, Z., Song, H., Watkins, D.W., Ong, K.G., Xue, P., Yang, Q., Shi, X., 2015. Cyber-physical systems for water sustainability: challenges and opportunities. IEEE Commun. Mag. 53, 216–222. https://doi.org/10.1109/MCOM.2015.7105668.
Watanabe, E.H., da Silva, R.M., Junqueira, F., dos Santos Filho, D.J., Miyagi, P.E., 2016. An emerging industrial business model considering sustainability evaluation and using cyber physical system technology and modelling techniques. IFAC-PapersOnLine 49, 135–140. https://doi.org/10.1016/j.ifacol.2016.12.203.
Watanabe, E.H., Silva, R.M., 2017. Assessment of sustainability for production

control based on petri net and cyber-physical cloud system. IFAC Pap. 50, 13527–13532. https://doi.org/10.1016/j.ifacol.2017.08.1808.
Watson, H.J., 2014. Tutorial: big data analytics: concepts, technologies, and applications. Commun. Assoc. Inf. Syst. 34, 1247–1268.
Welbourne, E., Battle, L., Cole, G., Gould, K., Rector, K., Raymer, S., Balazinska, M., Borriello, G., 2009. Building the internet of things using RFID: the RFID ecosystem experience. IEEE Internet Comput. 13, 48–55. https://doi.org/10.1109/MIC.2009.52.
Wright, P., 2013. Cyber-physical product manufacturing. Manuf. Lett. 2, 49–53. https://doi.org/10.1016/j.mfglet.2013.10.001.
Wu, D., Jennings, C., Terpenny, J., Gao, R.X., Kumara, S., 2017a. A comparative study on machine learning algorithms for smart manufacturing: tool wear prediction using random forests. J. Manuf. Sci. Eng. 139, 71018–71019. https://doi.org/10.1115/1.4036350.
Wu, D., Rosen, D.W., Wang, L., Schaefer, D., 2015. Cloud-based design and manufacturing: a new paradigm in digital manufacturing and design innovation. CAD Comput. Aid. Des. 59, 1–14. https://doi.org/10.1016/j.cad.2014.07.006.
Wu, K.J., Liao, C.J., Tseng, M.L., Lim, M.K., Hu, J., Tan, K., 2017b. Toward sustainability: using big data to explore the decisive attributes of supply chain risks and uncertainties. J. Clean. Prod. 142 (Part 2), 663–676. https://doi.org/10.1016/j.jclepro.2016.04.040.
Xie, H., Tong, X., Meng, W., Liang, D., Wang, Z., Shi, W., 2015. A multilevel stratified spatial sampling approach for the quality assessment of remote-sensing-derived products. IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 8, 4699–4713. https://doi.org/10.1109/JSTARS.2015.2437371.
Xu, D.F., Li, Q., Jun, H.B., Browne, J., Chen, Y.L., Kiritsis, D., 2009. Modelling for product information tracking and feedback via wireless technology in closed-loop supply chains. Int. J. Comput. Integr. Manuf. 22, 648–670. https://doi.org/10.1080/09511920701675755.
Xu, L. Da, He, W., Li, S., 2014. Internet of things in industries: a survey. IEEE Trans. Ind. Inf. 10, 2233–2243. https://doi.org/10.1109/TII.2014.2300753.
Xu, M., Cai, H., Liang, S., 2015. Big Data and industrial ecology. J. Ind. Ecol. 19, 205–210.
Xu, X., 2012. From cloud computing to cloud manufacturing. Robot. Comput. Integr. Manuf. 28, 75–86. https://doi.org/10.1016/j.rcim.2011.07.002.
Yang, D., Eastman, C.M., 2007. A rule-based subset generation method for product data models. Comput. Civ. Infrastruct. Eng. 22, 133–148. https://doi.org/10.1111/j.1467-8667.2006.00476.x.
Yue, X., Cai, H., Yan, H., Zou, C., Zhou, K., 2015. Cloud-assisted industrial cyber-physical systems: an insight. Microprocess. Microsyst. 39, 1262–1270. https://doi.org/10.1016/j.micpro.2015.08.013.
Zampou, E., Plitsos, S., Karagiannaki, A., Mourtos, I., 2014. Towards a framework for energy-aware information systems in manufacturing. Comput. Ind. 65, 419–433. https://doi.org/10.1016/j.compind.2014.01.007.
Zareian, S., Fokaefs, M., Khazaei, H., Litoiu, M., Zhang, X., 2016. A big data framework for cloud monitoring. In: Proceedings of the 2nd International Workshop on BIG Data Software Engineering, pp. 58–64.
Zehtaban, L., Elazhary, O., Roller, D., 2016. A framework for similarity recognition of CAD models. J. Comput. Des. Eng. 3, 274–285. https://doi.org/10.1016/j.jcde.2016.04.002.
Zeng, Y., Wang, L., 2010. A hybrid decision support system for slow moving spare parts joint replenishment: a case study in a nuclear power plant. Int. J. Comput. Appl. Technol. 37, 287–296.
Zhang, F., Luk, T., 2007. A data mining algorithm for monitoring PCB assembly quality. IEEE Trans. Electron. Packag. Manuf. 30, 299–305. https://doi.org/10.1109/TEPM.2007.907576.
Zhang, G., Zhang, Y., Xu, X., Zhong, R.Y., 2018f. An augmented Lagrangian coordination method for optimal allocation of cloud manufacturing services. J. Manuf. Syst. 48, 122–133. https://doi.org/10.1016/j.jmsy.2017.11.008.
Zhang, Y., Guo, Z., Lv, J., Liu, Y., 2018a. A framework for smart production-logistics systems based on CPS and industrial IoT. IEEE Trans. Ind. Inf. 14, 4019–4032. https://doi.org/10.1109/TII.2018.2845683.
Zhang, Y., Liu, S., Liu, Y., Yang, H., Li, M., Huisingh, D., Wang, L., 2018b. The 'Internet of Things' enabled real-time scheduling for remanufacturing of automobile engines. J. Clean. Prod. 185, 562–575. https://doi.org/10.1016/j.jclepro.2018.02.061.
Zhang, Y., Qian, C., Lv, J., Liu, Y., 2017a. Agent and cyber-physical system based self-organizing and self-adaptive intelligent shopfloor. IEEE Trans. Ind. Inf. 13, 737–747. https://doi.org/10.1109/TII.2016.2618892.
Zhang, Y., Ren, S., Liu, Y., Sakao, T., Huisingh, D., 2017b. A framework for Big Data driven product lifecycle management. J. Clean. Prod. 159, 229–240. https://doi.org/10.1016/j.jclepro.2017.04.172.
Zhang, Y., Ren, S., Liu, Y., Si, S., 2017c. A big data analytics architecture for cleaner manufacturing and maintenance processes of complex products. J. Clean. Prod. 142 (Part 2), 626–641. https://doi.org/10.1016/j.jclepro.2016.07.123.
Zhang, Y., Ma, S., Yang, H., Lv, J., Liu, Y., 2018c. A big data driven analytical framework for energy-intensive manufacturing industries. J. Clean. Prod. 197, 57–72. https://doi.org/10.1016/j.jclepro.2018.06.170.
Zhang, Y., Wang, J., Liu, Y., 2018d. Game theory based real-time multi-objective flexible job shop scheduling considering environmental impact. J. Clean. Prod. 167, 665–679. https://doi.org/10.1016/j.jclepro.2017.08.068.
Zhang, Y., Zhang, G., Qu, T., Liu, Y., Zhong, R.Y., 2017d. Analytical target cascading for optimal configuration of cloud manufacturing services. J. Clean. Prod. 151, 330–343. https://doi.org/10.1016/j.jclepro.2017.03.027.
Zhang, Y., Zhang, G., Wang, J., Sun, S., Si, S., Yang, T., 2015. Real-time information capturing and integration framework of the internet of manufacturing things. Int. J. Comput. Integr. Manuf. 28 (8), 811–822. https://doi.org/10.1080/0951192X.2014.900874.
Zhang, Y., Zhu, Z., Lv, J., 2018e. CPS-based smart control model for shopfloor material handling. IEEE Trans. Ind. Inf. 14, 1764–1775. https://doi.org/10.1109/TII.2017.2759319.
Zhang, Z., Chu, X., 2009. A new integrated decision-making approach for design alternative selection for supporting complex product development. Int. J. Comput. Integr. Manuf. 22, 179–198.
Zhao, R., Liu, Y., Zhang, N., Huang, T., 2017a. An optimization model for green supply chain management by using a big data analytic approach. J. Clean. Prod. 142 (Part 2), 1085–1097. https://doi.org/10.1016/j.jclepro.2016.03.006.
Zhao, Y., Liu, Q., Xu, W., Wu, X., Jiang, X., Zhou, Z., Pham, D.T., 2017b. Dynamic and unified modelling of sustainable manufacturing capability for industrial robots in cloud manufacturing. Int. J. Adv. Manuf. Technol. 93, 2753–2771. https://doi.org/10.1007/s00170-017-0634-1.
Zheng, H., Feng, Y., Tan, J., 2017a. A hybrid energy-aware resource allocation approach in cloud manufacturing environment. IEEE Access 5, 12648–12656. https://doi.org/10.1109/ACCESS.2017.2715829.
Zheng, M., Wu, K., 2017. Smart spare parts management systems in semiconductor manufacturing. Ind. Manag. Data Syst. 117, 754–763. https://doi.org/10.1108/IMDS-06-2016-0242.
Zheng, P., Lin, T.J., Chen, C.H., Xu, X., 2018a. A systematic design approach for service innovation of smart product-service systems. J. Clean. Prod. 201, 657–667. https://doi.org/10.1016/j.jclepro.2018.08.101.
Zheng, P., Lin, Y., Chen, C.-H., Xu, X., 2018b. Smart, connected open architecture product: an IT-driven co-creation paradigm with lifecycle personalization concerns. Int. J. Prod. Res. 1–14. https://doi.org/10.1080/00207543.2018.1530475.
Zheng, Z., Xu, W., Zhou, Z., Pham, D.T., Qu, Y., Zhou, J., 2017b. Dynamic modeling of manufacturing capability for robotic disassembly in remanufacturing. Procedia Manuf. 10, 15–25. https://doi.org/10.1016/j.promfg.2017.07.005.
Zhong, R.Y., Dai, Q.Y., Qu, T., Hu, G.J., Huang, G.Q., 2013. RFID-enabled real-time manufacturing execution system for mass-customization production. Robot. Comput. Integr. Manuf. 29, 283–292. https://doi.org/10.1016/j.rcim.2012.08.001.
Zhong, R.Y., Newman, S.T., Huang, G.Q., Lan, S., 2016. Big Data for supply chain management in the service and manufacturing sectors: challenges, opportunities, and future perspectives. Comput. Ind. Eng. 101, 572–591. https://doi.org/10.1016/j.cie.2016.07.013.
Zhong, R.Y., Xu, C., Chen, C., Huang, G.Q., 2017. Big data analytics for physical internet-based intelligent manufacturing shop floors. Int. J. Prod. Res. 55, 2610–2621. https://doi.org/10.1080/00207543.2015.1086037.
Zhou, K., Fu, C., Yang, S., 2016. Big data driven smart energy management: from big data to big insights. Renew. Sustain. Energy Rev. 56, 215–225.
Zhu, Q., Wu, J., Song, M., 2018. Efficiency evaluation based on data envelopment analysis in the big data context. Comput. Oper. Res. 98, 291–300. https://doi.org/10.1016/j.cor.2017.06.017.
Zhuang, C., Liu, J., Xiong, H., 2018. Digital twin-based smart production management and control framework for the complex product assembly shop-floor. Int. J. Adv. Manuf. Technol. 96, 1149–1163. https://doi.org/10.1007/s00170-018-1617-6.
Zikopoulos, P., DeRoos, D., Parasuraman, K., Deutsch, T., Corrigan, D., Giles, J., 2013. Harness the Power of Big Data: the IBM Big Data Platform. McGraw Hill Professional. https://doi.org/10.1007/s13398-014-0173-7.2.
Zuo, Y., Tao, F., Nee, A.Y.C., 2018. An Internet of things and cloud-based approach for energy consumption evaluation and analysis for a product. Int. J. Comput. Integr. Manuf. 31, 337–348.