Available online at www.sciencedirect.com

ScienceDirect

Procedia CIRP 55 (2016) 290 – 295

www.elsevier.com/locate/procedia

5th CIRP Global Web Conference Research and Innovation for Future Production

Industrial Big Data as a result of IoT adoption in Manufacturing

D. Mourtzis*, E. Vlachou, N. Milas

Laboratory for Manufacturing Systems and Automation (LMS), University of Patras, Rion Patras 26500, Greece

* Corresponding author. Tel.: +30-2610-997262; fax: +30-2610-997744. *E-mail address:* mourtzis@lms.mech.upatras.gr

Abstract

The radical evolution of internet into a network of interconnected objects that create a smart environment is characterized by the term Internet of Things (IoT). The adoption of IoT in manufacturing enables the transition of tradition manufacturing systems into modern digitalized ones, generating significant economic opportunities through industries re-shaping. Industrial IoT empowers the modern companies to adopt new data-driven strategies and handle the global competitive pressure more easily. However, the adoption of IoT, increases the total volume of the generated data transforming the industrial data into industrial Big Data. The work demonstrated in this paper presents how the adoption of IoT in manufacturing, considering sensory systems and mobile devices, will generate industrial Big Data. Moreover, a developed IoT application is presented showing how real industrial data can be generated leading to Industrial Big Data. The proposed methodology is validated in a real life case study from a mould-making industry.

Peer-review under responsibility of the scientific committee of the 5th CIRP Global Web Conference Research and Innovation for Future Production

Keywords: IoT, Monitoring, Big Data, Manufacturing

1. Introduction

With the advent of the fourth industrial revolution manufacturing systems are transformed into digital ecosystems. In this transformation, the Internet of Things (IoT) and Big Data pose a major role. Towards that end, industrial enterprises have entered a new age of “Big Data”, where the volume, velocity and variety of data they manage is exploding at really high rates [1]. The IoT, which describes a network of interconnected objects through embedded technology, will feed directly into Big Data concept by enabling the collection of even more information [2]. More and more devices, manufacturing tools, plants, vehicles, as well as manufacturing equipment are equipped with sensors.

In modern industries, data generated by sensors embedded in machine tools, cloud-based solutions as well as business management has already reached a total volume of more than 1000 Exabytes annually and is expected to increase the next years [3]. The digital transformation of industry empowered by the IoT adoption allows new ways for businesses to connect and co-create value. New data-driven strategies will support the companies to optimize their performance by gathering and analyzing data through the whole product lifecycle.

Moreover, forward- thinking companies can exploit the generated data in order to create an advantage and increase their competitiveness through predictive analysis [2, 4]. One of the main challenges of Big Data analytics is the visualization of the results. New approaches for context-aware visualization should be followed in order to sufficiently support the decision-making in the different levels of an enterprise.

Despite the high level of IoT adoption in manufacturing, cost-efficient and plug-and-play approaches that will allow systems interoperability, are still missing. The proposed work presents how the adoption of IoT in manufacturing will generate Industrial Big data. Moreover, a cost-efficient, non-disruptive IoT application for SMEs is presented exploring the high volume of data that can be generated.

Peer-review under responsibility of the scientific committee of the 5th CIRP Global Web Conference Research and Innovation for Future Production
doi:10.1016/j.procir.2016.07.038

2. State of the Art

The evolution of manufacturing science and technology, along with the recent advances in computer sciences and the information-communication technologies are the basic pillars for the adoption of Cyber-Physical Systems (CPS) in industry, also known as Cyber-Physical Production Systems (CPPS) [5]. CPS link the physical world seamlessly with the virtual world of information technology and software [6], and by doing so, use various types of available data, digital communication facilities, and services [7]. However, the adoption of CPS by applying IoT, especially in industry, results into the creation of vast amounts of information that needs special manipulation and analysis in order to perform meaningful reasoning and extract the actual value. To meet this challenge, the big data analytics is a facilitator to overcome the bottlenecks that are created by the data generated by IoT.

The radical evolution of the internet into a network of interconnected objects that create a smart environment is characterised by the term Internet of Things. The definition of IoT that is be adopted in this study is “The Internet of Things allows people and things to be connected Anytime, Anyplace, with Anything and Anyone, ideally using Any path/network and Any service” [8]. In industry the term Industrial IoT (IIoT) is introduced and refers to the application of IoT in industry and implies the use of sensors and actuators, control systems, machine-to-machine, data analytics, and security mechanisms. Many significant applications of industrial IoT are emerging. IIoT can strengthen modern industries with the three pillars i.e. the process optimisation, the optimised resource consumption, and the creation of complex autonomous system [9]. The IoT is a multi-disciplinary field. In [10] the authors state that the IoT paradigm is a result of the convergence of the visions that are Internet-oriented, semantic-oriented, and embedded electronics-oriented.

The CPS paradigm suggests the use of monitoring devices under the IoT philosophy that go beyond the traditional approaches for on-site data collection, processing, and visualisation. The necessity for the use of real-time monitoring in manufacturing has been stressed in the work of [11]. The authors identified that the main requirements for monitoring systems in production are the robustness, the capability for reconfiguration, the reliability, the intelligence, and the cost efficiency. Various topologies for the communication of monitoring devices can be employed. In manufacturing the wireless sensor network topologies are the most eligible candidates as they offer flexibility and scalability, especially in flexible environments such as the shop-floors [12]. A wireless sensor network (WSN) consists of a large number of wireless-capable sensor devices working collaboratively to achieve a common objective [13]. In the context of manufacturing systems, the sensors that are monitoring the production can compose a WSN with the objective to increase or reduce production KPIs.

In previous literature, monitoring systems supported by WSN for the purposes of maintenance [14,15], energy and remaining useful life estimation [16,17], and cutting tool reconditioning [18], adaptive scheduling [19], adaptive process planning [20], among other, are reported.

One of the most important outcomes of the emerging of IoT is the generation of large volumes of data, which by 2020 will be over 40 trillion gigabytes (or 40 yottabytes), and need special manipulation to provide meaningful information [21]. According to Gartner predictions there will be nearly 20 billion devices connected to the IoT by 2020 and a large majority of them will come from the industrial sector. This information can conclude to knowledge enhancement and insights into many critical aspects leading to the era of Big Data. The basic characteristics that make Big Data unique are the high volume, velocity, and variety of information; although new characteristics are being continuously introduced with value being the most important [22]. Furthermore, the identification of patterns is very important in order to conclude to predictions decisions [23].

New technologies, such as Cloud computing, enable the analysis of Big Data through the Internet providing ubiquitous access to information [24]. Cloud technologies, and especially the philosophy of Cloud manufacturing, act as enablers for the ubiquitous access to information and the collaboration among different IT tools. An extensive literature review on Cloud manufacturing has been performed by [25,26]. The authors examine the current usage of Cloud computing in manufacturing phases and conclude the literature review presenting a conceptual framework with core elements being the Cyber-physical systems, Smart sensor networks, Big Data analysis, and Cloud computing. Cloud manufacturing can support the realisation of “Design Anywhere Manufacture Anywhere” philosophy, providing scalability to business size and needs, ubiquitous network access, and visualisation [27].

Big Data analytics has also to play role in the realization of the idea of Digital manufacturing by acting as an enabler for technologies like additive manufacturing [28]. Furthermore, Big Data analytics constitute the basis for the modern scope of mass customization, which implies the fulfilling of the needs of individualized customer markets [29]. In applications such as prognostics and health management for manufacturing systems the acquired data has to be evaluated before considered valid [30]. The analysis of large sets of data can enhance the knowledge repositories and improve decision making in different manufacturing stages, such as assembly operations [31]. Other sources of data that need to be taken into consideration are the intelligent products. With the use of product embedded information devices (PEID), such as RFID, the products hold information about their lifecycle.

The value of Big Data for manufacturing are exhibited in a recent survey by McKinsey Global Inc; the report claimed that Big Data exploitation in manufacturing can decrease product development and assembly costs by up to 50% and can cause a 7% reduction in working capital [32]. In such an environment, CPS can be further developed for managing Big Data and leveraging the interconnectivity of machines to reach the goal of intelligent, resilient and self-adaptable machines. Also, data analytics have to change from being centralised, structured, and static to being distributed, mixed structured, and real-time [33].

The literature survey makes apparent that modern industries should be shifted towards digitalization in order to increase their performance and competitiveness. However, digitalization, as expressed though CPS, IoT, Cloud as well as Big Data, and its relevant enabling technologies should be further investigated in order to address existing as well as future manufacturing challenges. Among, the most important challenges are to establish agreed-upon standards for connectivity and security to ensure a future of IoT technologies that can communicate and collaborate instead of existing in their own standalone ecosystems. Moreover, another main challenge, is the handling of Big Data generated from the diverse sources of a manufacturing system using Big Data analytic techniques to support decision making. The management and visualisation of data from heterogeneous data sources under one platform is one of the major challenges that need to be addressed in digitalised factories. The proposed work presents a developed IoT application and demonstrates how digitalization of factories and enterprises will generate industrial Big Data.

3. Industrial Big Data as a result of IIoT adoption in Manufacturing

In modern industries, data generated by sensors embedded in machine tools, cloud-based solutions as well as business management are continuously increasing. Following the work presented by Batty et. al, it is expected that industrial data has reached a total volume of more than 1000 Exabytes annually [3]. Compared with the size of Big Data reported by Google, or Cisco, this data is of lower volume, however, it tends to be increased the next years. For that reason, in this work, the data that is generated from industry by the adoption of IoT paradigm, is called “Industrial Big Data”, and not “Big Data”. The main goal of IoT adoption in manufacturing is to realize smart factories, in which machines and resources communicate and are connected in a network. To achieve that, machine tools, resources as well as existing IT tools of an enterprise should be connected to the internet directly or through external adapters. As a result, machine tools will be transformed into “cyber-machine tools” enriched with knowledge provided by the data capturing and analysis. In addition to the above, resources considering also human operators will be connected to the internet network by using mobile devices, transforming operators into “Cyber-Operators”. Finally, existing IT tools and business management tools will be connected to the network, capturing heterogeneous data from different sources. Such a smart enterprise will produce intelligent products (smart products) that know how they have been produced, and will collect and transmit data as they are being used; these huge amounts of data (big data) will be collected and analysed [33].

Data generated by the lower level of an enterprise, directly from the machine tools and the human operators is of high importance for an enterprise, as this data can be used and analysed in order to provide meaningful information to the higher levels of the enterprise making them adaptive and flexible.

As a result, specific focus should be given in transforming the basis of the production systems into cyber-physical production systems. A main challenge towards this transformation is the design and development of standard and secure communication protocols capable of interfacing existing systems and collecting and exchanging manufacturing data. An IoT application, supported by a WSN and designed upon a standard industrial communication protocol is described below, presenting how Industrial Big Data can be generated (Fig. 1).

3.1. Monitoring system via WSN

In this study, a monitoring tool organized in a wireless sensor network (WSN) is presented. The monitoring tool consists of a data acquisition (DAQ) device which utilizes split-core current transformers (CT) as current sensors, a closed-loop hall effect current sensor, as well as a camera. These sensors are selected in order to create a non-intrusive and easy to install application for monitoring the status of machine-tools. The proposed tool is designed as an add-on for the commercial machine-tools, rather than communicating with the machine controller. This decision is mainly driven by the fact that the lifespan of the industrial equipment can reach the 50 years [19], hence old machinery often do not have the required capabilities for connectivity. Therefore, special effort is required to transform each legacy controller into an IoT device.

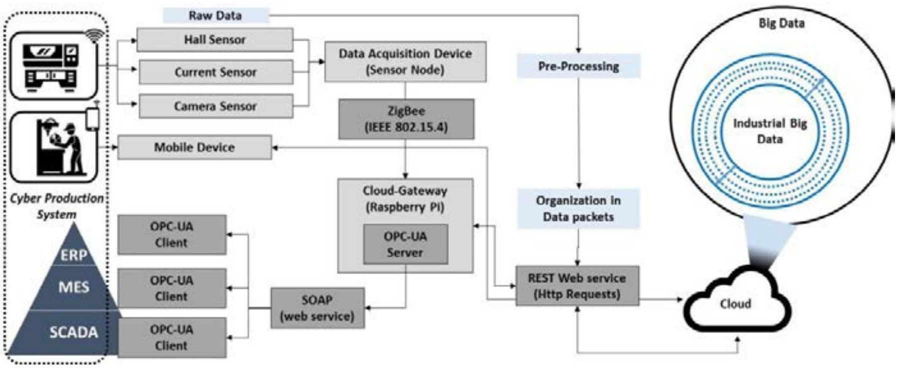

Fig. 1 Industrial Big Data generated by the developed IoT application

The main objective of the developed DAQ is to identify correctly the status of the machine-tool in real time, as well as to provide energy consumption related measurements and insights related to potential failures. For this reason, current sensors measure the currents of the main motor drives, and current and voltage sensors are employed to measure the overall power consumption. The sampling rate for the sensors on the axes and the overall power consumption is 1 ksps and for the spindle is 1 MHz. The samples gained by the sensor on the spindle are processed through a Fast Fourier Transform (FFT) to provide the footprint of the machine and identify deviations in the case of malfunctions.

The DAQs of a shop-floor are organised in a (WSN) following the star topology. The selection of the WSN was driven by the requirements for flexibility and reduced infrastructure. The data transmission is coordinated by a central gateway which is responsible to collect the data from the DAQs and organise them into packets before transmitting them to a Cloud server for further processing and visualisation.

The WSN is facilitated with the use of DIGI XBee ZigBee RF module. The selection of ZigBee over other wireless standards is performed due to its support to various network topologies and encryption algorithms, and its robust operation with functionalities such as collision avoidance, retries, and acknowledgements performed in the hardware.

Except from the data acquisition device, a mobile device is considered for the machine tool operator. Through the mobile device, the human operator can provide different information related to the machine tool and to the running tasks. The results are aggregated in the Cloud server and are visualised along with a set of performance indicators. The above mentioned IoT-based monitoring tool is designed to support integration with other existing industrial equipment and IT tools. The OPC Unified Architecture (UA) standard has the potential to support integration of equipment of different vendors and architecture towards realising the Industry 4.0 vision [34], with more than 48% OPC foundations member companies in Europe [35]. Moreover, it can provide communications in all levels of manufacturing enterprises, from the resource to the factory level, via a service oriented

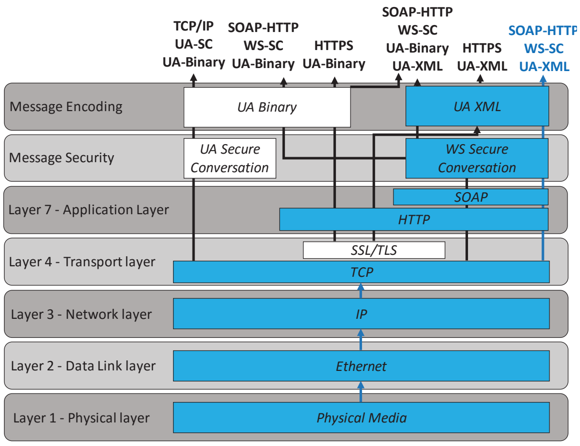

Fig. 2 Mapping OPC-UA to the Open Systems Interconnection (OSI) model

architecture [36]. The OPC-UA provides an extensible data model which provides the data schema. As a result, even systems that are not familiar with the data model can retrieve information from other systems. In the OSI model the OPC-UA is implemented on top of TCP layer (Fig. 2) [26]. In the proposed system the microcomputer acts as an OPC-UA server with XML encoding in a SOAP Web-service [37]. The information model follows the specification and is designed to correspond to the schema of the designed database (Fig. 3) of the IoT application. Moreover, considering the variety of the devices that will be integrated to the central servers and the different data formats that will be incorporated, the creation of the databases is not a trivial task. Due to the ever-increasing requirements, flexibility in the database schemas are required. Therefore, for these purposes, non-relational (NoSQL) databases are more convenient compared to relational (SQL) databases that are not flexible when changes in the schema are required.

Subsequently, the Cloud server employs a MongoDB NoSQL database for the storage of the sensor data from the DAQs.

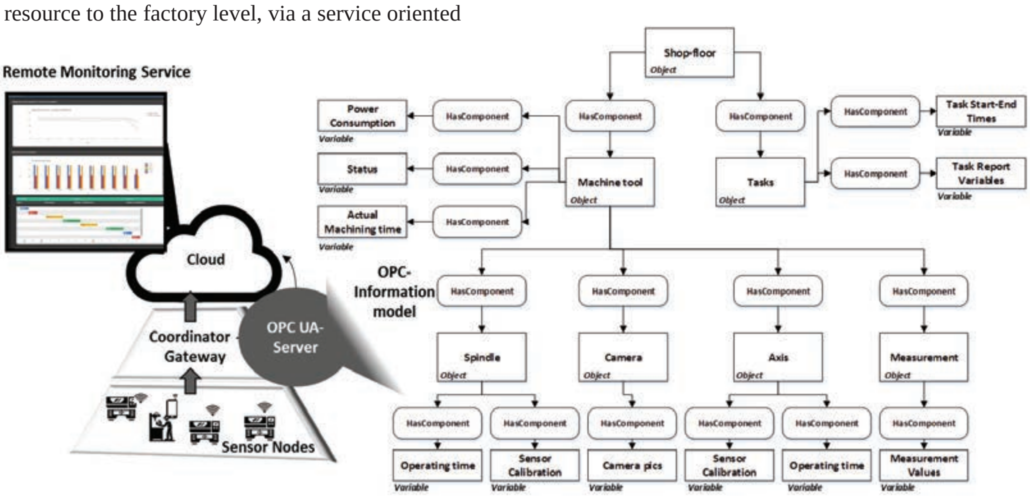

Fig. 3 The developed Monitoring Service as an IoT paradigm

The microcomputer transmits the generated data to the Cloud service through a REST service using HTTP requests [38]. Security was a major concern during the development of the monitoring service in the Cloud, and was applied to three layers, namely, the shop-floor, the web application, and the Cloud service operating system layers. In these layers, there is a variety of counter measures against different threats such as encryption during data transfer, identification of clients through Secure Sockets Layer (SSL) and Transport Layer Security (TLS) protocols, used along with a secure database authentication system and the Virtual Private Network (VPN) technology [20].

4. Case study and Results

The developed IoT application is applied in a mould-making industry which has 100 machine tools and 150 employees, in order to demonstrate how industrial data can be generated and how they can lead to Industrial Big Data. The developed tool has been applied in one machine tool and the data that were captured and transmitted to the gateway, were measured in order to identify the volume of the generated data. The camera is assumed for 10 machine-tools which were the most crucial for the production. Once the generated data was measured per machine tool, a total volume of the generated data from the whole shop-floor was calculated, demonstrating how much data can be generated in a shop-floor using the aforementioned types of sensors. This results into a volume of generated data that is presented in (Table 1) along with the sampling rate for each sensor that is employed. The firmware of the proposed monitoring tool is designed in order to provide and transmit to the Cloud processed data with transmission rate of 4 measurements per second. Based on this rate, the table below presents the meaningful data that are the result of the processing on the DAQ (Table 2). The industrial data presented in Table 2 are generated taking into account the different types of sensors employed in the IoT tool, engineering data, as well as business data generated in the case of the mould–making industry. In our case study, the selected transmission rate of the generated data is based on the nature of the production of the mould- making industry.

To have a holistic view of the issue in the mould-making company, the engineering related data and the business related data in the time period of one year where reported.

Table 1 Data generated by the developed DAQ

DAQ Level –Generated data		
Sensor	**Sampling rate**	**Megabytes per hour**
Spindle Closed-loop Hall sensor	**1 MHz**	**13,733**
Axis X split-core CT	**1 kHz**	**13.73**
Axis Y split-core CT	**1 kHz**	**13.73**
Axis Z split-core CT	**1 kHz**	**13.73**
Mains current split-core CT	**1 kHz**	**13.73**
Mains voltage insulation transformer	**1 kHz**	**13.73**
Camera	**10 screens/min**	**293**
SUM	**-**	**14,095**

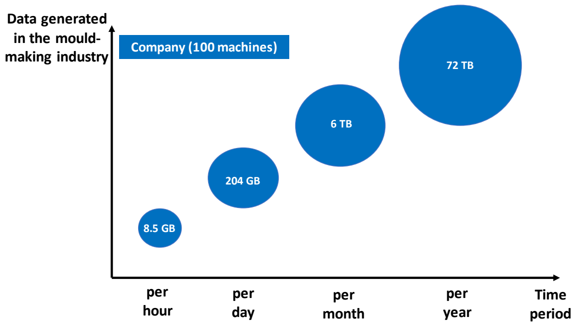

Fig. 4 Industrial Big Data generated by the adoption of the developed IoT application

The engineering data include all the necessary documentation of the products from the manufacturing perspective. Additionally, the business data consider data from the IT tools (ERP, accounting software) and communication software (i.e. emails). Nevertheless, the volume of these data was found to be an order of magnitude less than the data from the IoT. The data generated from the mobile devices were not considered due to their low volume and frequency. If we consider data from a variety of IoT tools, the data from the mobile devices of the human operators, as well as data from various and different IT tools in the company that can be interfaced through the OPC-UA architecture described in 3.1, a high volume and variety of data will be considered reaching the start point for Industrial Big Data (Fig. 4).

The main aspects of the Industrial Big Data are not found inside one company but in a network of interconnected companies were different data should be collected and transmitted in order to process them and derive meaningful insights for adaptive and flexible decision-making. To demonstrate that, a scenario of 50 interconnected companies in a manufacturing network was considered in order to show that real industrial Big Data, in the volume that are reported also by global reports, can be reached in a network level.

Table 2 Industrial Data Transmitted

Data source	Generated Data/day	Generated Data/month	Generated Data/year
Machine tool	1,356MB	39.73GB	0.47TB
Camera	7,200MB	211GB	2.47TB
Shop-floor (100 machine tools, camera in 10)	**204GB**	**6TB**	**72TB**
Production network (50 industries)	**10TB**	**300TB**	**3.6EB**

Following that, one of the main challenges of Industrial Big Data is to gather and consider only the most important data for each decision that has to be made. Through the proposed monitoring system data can be processed in the local level the machine tools nodes as well as the microcomputer in order to reduce the volume of data that will transmitted and stored into the Cloud database. Moving towards, this direction the actual data that will be transmitted will not be of high volume and as a result quick and efficient decision will be made.

5. Conclusions

The proposed work presents how the adoption of IoT paradigm in manufacturing will generate Industrial Big Data. Industrial Big Data compared with the size of Big Data reported by Google, or Cisco, is of lower volume, however, it tends to be increased the next years. Industries are facing a new era of IoT. New monitoring services and the concept of IoT that tends to transform the machine tools into "cyber-machine tools" and the human operator into a "cyber - operator" will generated high volume and variety of data. In addition to that, new industrial communication protocols, such as OPC-UA will empower the interface with existing IT tools and will enable quick and accurate communication.

The IoT paradigm transform the industries into "cyber-production systems" capable of being flexible and adaptive and fully aware on the production conditions. However, new way of filtering and processing the data should be considering in order to reduce the produced and transmitted data. The proposed work shows how the IoT paradigm in a simple case of a company of 100 machine tools considering different types of sensors can produce data and can lead to Industrial Big Data.

Acknowledgements

The work presented in this paper is partially supported by the EU funded research project "Collaborative and Adaptive Process Planning for Sustainable Manufacturing Environments − CAPP4SMEs" (314024).

References

[1] General Electric Report, The Rise of Industrial Big Data, 2012.
[2]ICTC, Big Data & The Intelligence Economy, Accessed by http://www.ictc-ctic.ca/wp-content/uploads/2015/12/BIG-DATA-2015.pdf
[3] Bailly M, Manyika J, Is manufacturing 'cool' again?, McKinsey Global Inst., Jan. 21, 2013.
[4] Chryssolouris G, Manufacturing Systems: Theory and Practice. 2nd New York: Springer-Verlag; 2006.
[5] Monostori L, Cyber-physical Production Systems: Roots, Expectations and R&D Challenges, Procedia CIRP, 2014;17:9-13.
[6] Sztipanovits J, Ying S, Strategic R&D opportunities for 21st century, Cyber-physical systems, Connecting computer and information systems with the physical world, Report, 2013.
[7] Mikusz M, Towards an Understanding of Cyber-Physical Systems as Industrial Software-Product-Service systems, Procedia CIRP, 2014;16:385-389
[8] Guillemin P, Friess P, Internet of things strategic research roadmap, The Cluster of European Research Projects, Tech. Rep., September 2009, http://www.internet-of-things-research.eu/pdf/IoT Cluster Strategic Research Agenda 2009.pdf
[9] McKinsey Quarterly, "The Internet of Things," Report, 2010. http://www.mckinsey.com/industries/high-tech/our-insights/the-internet-of-things
[10] Atzori L, Iera A, Morabito G, The Internet of Things: A survey, Computer Networks, 2010;54/15:2787-2805.
[11] Teti R, Jemielniak K, O'Donnell G, Dornfeld D, Advanced monitoring of machining operations, CIRP Annals – Manufacturing Technology, 2010;59/2:717-739.
[12] Wright P, Cyber-physical product manufacturing, Manufacturing Letters, 2014;2/2:49-53.
[13] Yingshu Li, My T. Thai, Weili Wu, Wireless Sensor Networks and Applications, Springer, 2008.
[14]Mourtzis D, Vlachou E, Milas N, Xanthopoulos N, A cloud-based approach for maintenance of machine tools and equipment based on shop-floor monitoring, Procedia CIRP, 2015;41:655-660.
[15]Jardine AKS, Lin D, Banjevic D, A review on machinery diagnostics and prognostics implementing condition-based maintenance,Mechanical System and Signal Processing, 2006;20/7:1483-1510.
[16]Si XS, Wang W, Hu CH, Zhou DH, Remaining useful life estimation – A review on the statistical data driven approaches, European Journal of Operating Research, 2011;213/1:1-14.
[17]Mourtzis D, Vlachou E, Milas N, Dimitrakopoulos G, Energy consumption estimation for machining processes based on real-time shop floor monitoring via wireless sensor networks, CIRP CMS 2016), 2016.
[18] Tapoglou N, Mehnen J, Vlachou A, Doukas M, Milas N, Mourtzis D, Cloud based platform for optimal machining parameter selection based on function blocks and real time monitoring. ASME. J. Manuf. Sci. Eng. doi:10.1115/1.4029806.
[19]Mourtzis D, Vlachou E, Doukas M, Kanakis N, Xanthopoulos N, Koutoupes A (2015) Cloud-Based Adaptive Shop-Floor Scheduling Considering Machine Tool Availability. ASME 2015 Houston, Texas.
[20]Mourtzis D, Vlachou E, Xanthopoulos N, Givehchi G, Wang L, Cloud based- adaptive process planning considering availability and capabilities of machine tools, Journal of Manufacturing Systems, 2016;39:1-8.
[21] Beñat Bilbao-Osorio, Dutta S, Lanvin B, Rewards and Risks of Big Data, The Global Information Technology Report, 2014. Available: http://www3.weforum.org/docs/WEF_GlobalInformationTechnology_Report_2014.pdf
[22]Gandomi A, Haider M, Beyond the hype: Big data concepts, methods, and analytics, Int Journal of Information Management, 2015;35:137-144
[23] Philip Chen CL, Zhang CY, Data-intensive applications, challenges, techniques and technologies: A survey on Big Data, Information sciences, 2014;275:314-347.
[24] Hashem IAT, Yaqoob I, Anuar NB, Mokhtar S, Gani A, Khan SU, The rise of "big data" on cloud computing: Review and open research issues, Information Systems, 2015;47:98-115.
[25] Mourtzis D, Schoinochoritis B, Vlachou E, A New Era of Web Collaboration: Cloud Computing and its Applications in Manufacturing, TQM 2015, ISBN: 978-86-7083-858-1, 2015.
[26]Mourtzis D, Vlachou E, Cloud-based Cyber-physical Systems and Quality of Services, TQM Emerald Journal , Volume 28, Issue 6(2016)
[27] Xu X, From cloud computing to cloud manufacturing, Robotics and Computer-Integrated Manufacturing, 2012;28/1:75-86.
[28]Tien JM, Big Data: Unleashing information, Journal of System Sciences and Systems Engineering, 2013;22:127-151.
[29] Tien JM, The next industrial revolution: Integrated services and goods, Journal of System Sciences and Systems Engineering, 2012;21:257-296.
[30] Chen X, Cheng K, Wang C, Design of a smart turning tool with application to in-process cutting force measurement in ultraprecision and micro cutting, Manufacturing Letters, 2014;2:112-117.
[31] Renu RS, Mocko G, Koneru A, Use of Big Data and Knowledge Discovery to Create Data Backbones for Decision Support Systems, Procedia Computer Science, 2013;20:446-453.
[32] McKinsey Global Institute, "Big data: The next frontier for innovation, competition, and productivity," Report, January 2011. [33] IBM. (2014). "The rise of machine data: Are you prepared?", Available online: http://www-01.ibm.com/common/ssi/cgi-bin/ssialias?subtype=BK&infotype=PM&appname=SWGE_IM_EZ_USEN&htmlfid=IMM14142USEN&attachment=IMM14142USEN.PDF
[34] OPC Foundation, "OPC Unified Architecture - Pioneer of the 4th industrial (r)evolution," Report, 2014. Available at: https://jp.opcfoundation.org/wp-content/uploads/2014/03/OPC_UA_I_4.0_Pioneer_US_v2.pdf
[35] OPC Foundation, "OPC Unified Architecture –Interoperability Standard," Report, 2014. Available at: https://jp.opcfoundation.org/wp-content/uploads/2014/03/OPC_UA_Brochure_US_2013_v2.pdf
[36] Leitner SH, Mahnke W,. OPC UA - Service-Oriented Architecture for Industrial Applications, ABB Corporate Research Center, 2007.
[37]SOAP web service, http://www.service-architecture.com/articles/web-services/soap.html
[38]Restful Web Service, http://www.ibm.com/developerworks/library/ws-restful/