G Model
JMSY-644; No. of Pages 12
ARTICLE IN PRESS
Journal of Manufacturing Systems xxx (2018) xxx–xxx
Contents lists available at ScienceDirect
Journal of Manufacturing Systems
journal homepage: www.elsevier.com/locate/jmansys

Holistic approach to machine tool data analytics

Juergen Lenz [a], Thorsten Wuest [b,*], Engelbert Westkämper [a]

[a] Graduate School Advanced Manufacturing Engineering, University of Stuttgart, Nobelstr. 12, 70569 Stuttgart, Germany
[b] Benjamin M. Statler College of Engineering and Mineral Resource, West Virginia University, Morgantown, WV 26506, USA

ARTICLE INFO

Article history:
Received 22 December 2017
Received in revised form 26 February 2018
Accepted 12 March 2018
Available online xxx

Keywords:
Industry 4.0
Smart manufacturing
Machine tool data
Data analytics
Machine learning
Machine tool controller

ABSTRACT

Recent developments across all phases of the knowledge discovery process in the machine tool data analytics process call for a paradigm shift regarding how to combine the different analytics objectives. Several machine tool data analytics processes are carried out individually by different departments. They are highly dependent on the specific analytics objectives of the individual department. All these individual tasks make use of the data coming from the same source – the machine tool controller and connected sensors. One result of today's rather diverse machine tool data analytics landscape in many manufacturing companies is that we exhibit several pockets of expertise and large numbers of individual dedicated solutions. Hence, processes and structures tend be inefficient, e.g., exhibit redundant processes, and the exchange between the different domains is difficult. Manufacturers face heavy competition for manufacturing experts, interested and qualified in data analytics. Therefore, it is in their best interest to utilizing this scarce resource as efficiently and effectively as possible. In this paper, we discuss the current situation exhibited in machine tool data analytics in manufacturing. Based on these insights, we propose a holistic approach to machine tool data analytics in order to tackle some of the identified shortcomings of current practices. We propose combining the tasks and bundling up analytics objectives across different departments and/or functions at the production line, factory or even the supply chain level. To evaluate our proposed approach, we provide selected implementation examples following the identified analytics objectives, including cross-domain analytics that focus on the interface between domains. Following, we critically discuss our proposed approach focused on the associated potential benefits, challenges and limitations. Lastly, we conclude the paper and provide an outlook on further research.

1. Introduction

Across all industries, experts agree that data is an increasingly valuable resource. The Economist, Forbes and other news outlets recently stated that data replaced oil as the world's most valuable resource [1,2]. At the same time, manufacturing, once a more traditional industry is becoming more digital, connected and rapidly transforming towards smart manufacturing systems. Several initiatives focusing on this transformation across the globe are gaining traction. The most well known initiatives are Industry 4.0, started in Germany/Europe [3], Smart Manufacturing [4] with roots in the U.S. and the Smart Factory program, based in South Korea [5]. All these initiatives have one thing in common: they heavily emphasize the use of manufacturing and machine tool data as well as data-related technologies, like the Industrial Internet of Things (IIoT) [6], sensor networks [7], cyber-physical systems [8] and data analytics [9,10,61].

Establishing the means for Smart Manufacturing to becoming a reality is a high priority in the United States. The recent launch of the new Clean Energy Smart Manufacturing Innovation Institute (CESMII),[1] funded by the Department of Energy, and programs run by the National Institute of Standards and Technology (NIST)[2] and others are evidence that the topic is of high priority in the national agenda. Among the many related activities is the yearly NIST Smart Manufacturing workshop with its session on 'Smart Manufacturing Apps and Services Marketplaces'. The session is co-chaired by one of the authors, and both the chairs and many of the participants are part of CESMII. During these very productive sessions, a reoccurring topic with high priority for industry is how to establish interoperability as well as effective and efficient use of manufacturing data, mainly by means of advanced data analytics, across

* Corresponding author.
E-mail address: thwuest@mail.wvu.edu (T. Wuest).

[1] https://www.cesmii.org.
[2] https://www.nist.gov/topics/smart-manufacturing.

https://doi.org/10.1016/j.jmsy.2018.03.003

G Model
JMSY-644; No. of Pages 12
ARTICLE IN PRESS

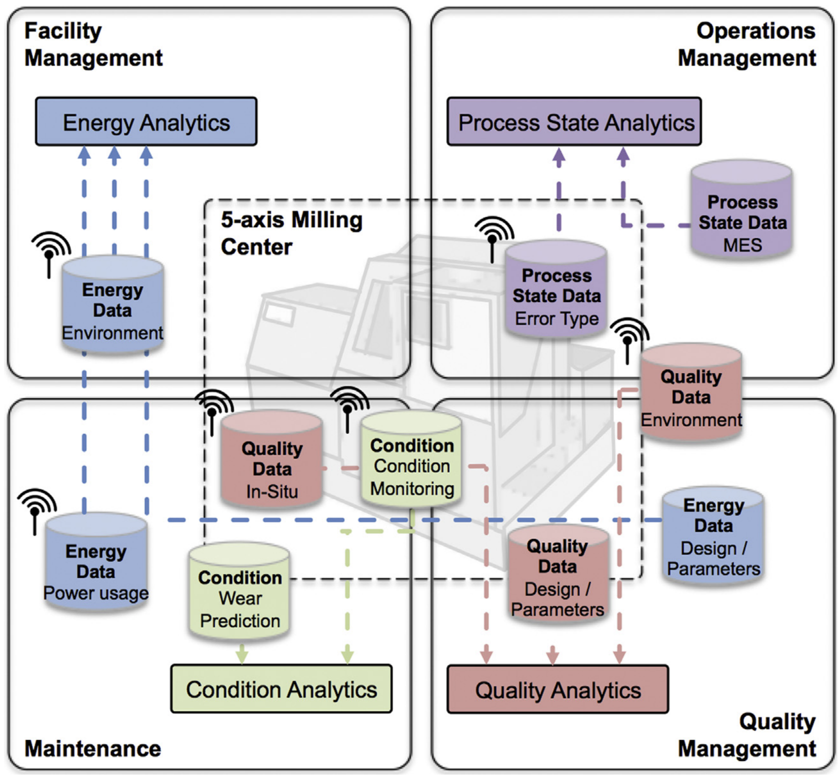

Fig. 1. Traditional approach to machine tool data analytics.

business units and domain borders [11]. In this paper, we present a holistic approach that is in line with the identified demand of Smart Manufacturing for the area of machine tool data.

Machine tool data in itself exhibits certain characteristics that are briefly explained in the following. The characteristics of machine tool data are the nonpermanent volatile nature of each variable (or parameter) value. They are continuously overwritten with each cycle of the controller. At the same time, they are also very time sensitive and only valid at one specific snapshot of the process. The specific values themselves have associated and clearly defined physical dimensions and are very precise due to their prior calibration process. The sensors used to capture the data have a high reliability. The values of the sensors are almost always plausible (correct) since the process itself could not be controlled with implausible (incorrect) measurements.

A critical look at the current state of the manufacturing industry reveals a discrepancy between how important the use of data is perceived and what is effectively being done in the data space to add real value. Leading researchers have recently reported on this gap (e.g., [12]). There are several factors that make the value adding adoption of data analytics in manufacturing challenging. Among them are the inherited complexity, dynamics and high-dimensionality of data that is regularly experienced within multi-stage manufacturing processes [13]. Furthermore, diverse manufacturing environment (e.g., exemplified by machine tools of multiple providers with various different PLCs, OS versions, sensor systems, protocols and age) is a challenge in itself with regard to the large variety of data that has to be collected, curated, quality checked, stored, analyzed and/or discarded. While the manufacturing industry has embraced technology for decades, the focus has been mainly on manufacturing technology and its physical manifestation, with little emphasis on the 'cyber' side including data analytics. Hence, there is a skills gap when it comes to a data centered mindset amongst the manufacturing workers.

The notion that new insights and knowledge can be derived solely by analyzing the available data is often neglected by expert manufacturing workers, especially on the shop floor. These expert workers have long-term experience in their field and acquired a deep understanding of the manufacturing processes they specialize in. One example of such domain expertise is the managing of heat treatment related distortion of large crankshafts, where an expert worker with years of experience is able to strategically place the heating blankets to prevent unwanted distortion. In most manufacturing domains, there is a certain understanding of the inter-dependencies between process parameters and process outcome, e.g., in form of physical models or simulations. Hence, the relatively well-defined system boundaries and the possibility to associate results with inputs prompted analytics in manufacturing to lean towards supervised machine learning techniques. In manufacturing, the teacher, as a manufacturing domain expert, and consequently labeled data (e.g., final quality measures) are more readily available than in most other domains [14] and the domain expertise is highly relevant when interpreting data. However, with progress in areas like deep learning and increased availability of large data sets (big data) this is changing and first results are very promising [15].

Another aspect is the availability of standards in communication and data processing. Currently, many providers of IIoT platforms, cloud solutions and other data analytics packages are aggressively working the market. While many of the systems and platforms provide some form of interface to each other and are adaptable/extensible by the users and third parties to some extent [16], common standards are needed [11]. In manufacturing value chains, the vertical integration of different business units and/or organizations require standards to effectively and efficiently exchange data. With MTConnect [17,18] a promising standard was introduced that is adopted quickly and seems to meet most of the different manufacturing industries' requirements. A second emerging standard is

Please cite this article in press as: Lenz J, et al. Holistic approach to machine tool data analytics. J Manuf Syst (2018), https://doi.org/10.1016/j.jmsy.2018.03.003