Impacts, Potentials, and Trends of Machine Learning in Industry 4.0: An Overview

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Abstract

Intelligent techniques has been required at the Industry 4.0 to integrate resources, data and technology. Many manufacturing problems can use machine learning to improve the service or product by analyzing, learning and correlating data stored in large databases. Thus, machine learning is essential to predict the process lead time, which is a fundamental parameter for the success of management and production planning and control. In addition, there is a range of machine learning applications in manufacturing problems that have not yet been fully investigated.

1. Introduction

In the current industrial scenario, there is a growing demand for the adoption of intelligent techniques, such as machine learning (ML) and artificial intelligence (IA) as an artifice for industries process to remain competitive in the era of Industry 4.0 and the emerging discussions of Industry 5.0 (Demir et al., 2019). Industry 4.0 provides the smarts manufacturing process through integrations of emerging digital intelligent technologies (Lins & Rabelo, 2019). It provides the integration of people, production systems, information and machines (Rauch et al., 2020). The term Industry 4.0 was created in Germany in 2011 and this new industrial revolution has been fast translated and inserted inside the most of country. Industry 5.0 boosts the human-robot co-working and provides the bioeconomy motivated by smart society and using renewable resources (Demir et al., 2019). Although the current industrial age is the fourth industrial revolution and the emergence of the fifth revolution have been rumored, many companies and sectors have not yet migrated to Industry 4.0 or at least adapted to all the technologies of the third revolution.

2. Applications of ML in Industry

The technologies of Industry 4.0 are interconnected by platforms that permit flexible, customized and quick response to market needs (Liu & Wang, 2020). In this context, the decision making supported by IA is driven mainly by adoption and improvement in ML in the Industry 4.0 (Sachan et al., 2019). Machine learning is especially applied into the engineering practices and manufacturing problems, mainly because some information or specification in intermediate or final actives in the process frequently need to be estimate from database. In general, ML can be applied into many sectors factories, such as sales, quality, logistic, customers, laboratories and services. In the 4.0 context, it can be used with the most technologies to improve the service or product by analyzing, learning, correlating and interpreting knowledge of large databases, such as Internet of things (IOT), cyber-physical systems, big data, and cloud computing (Romeo et al., 2020). Wang et al. (2020) applied ML to predict anaerobic digesters performance and critical operational parameters in the methane production. Also, ML helps to resolve challenges in the health care sector, such as to classify traumas disorders, diseases, treatment selection and predict outcomes (Lei et al., 2020). In addition, it can be applied to detect concrete defects, development of autonomous vehicle and traffic control, cybersecurity, mining patterns and anomalies, among many others.

3. ML to predict lead time process

An important application using ML, is the use of data mining, to predict the lead time process. In general, the lead time process is defined as the time between the order release and the product availability to the customer. Lead time is one the most essential parameters to successful of management and production planning and control into 3.0 and 4.0 process, including sum operation time and interoperation time such as transport time, setup time, material arrivals, and waiting time (Duffie et al., 2017). Consequently, the accuracy of lead time forecasting is fundamental because

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its uncertainty and instability can cause poor support and problems in the production planning and control systems, enterprise resource planning and manufacturing resource planning (Duffie et al., 2017). Incorrect lead time produces disruption and perturbation in process systems, such as short logistic achievement, wrong inventory control measures, short working in process and reduce the industry credibility. The value and lead time adjustments usually practiced can be understood in Figure 1.

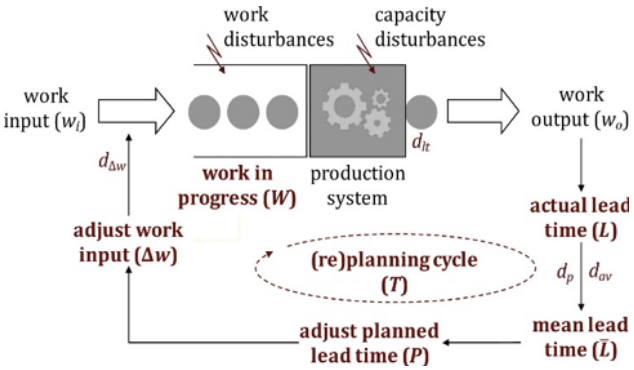

Figure 1. Usual estimation of lead time process in industry (Duffie et al., 2017).

The cycle presented in Figure 1 shows the lead time management (Duffie et al., 2017). Initially, the real lead time is measured counting the days, hours or minutes from the order until the product is available to the customer. After this, the average lead time from the historical database is calculated and it is used as a new lead time. Consequently, the use of mean lead time causes some problems in production management because there is a significant difference between the real lead time and mean lead time. Besides, most parameters and decision in the Production Planning and Control and production systems need to be recalculated and adjusted. Also, lead time prediction is a classical control problem in industries and scientific research. The main disadvantage of mathematical methods is considering the past trends will be happening in the future.

4. Conclusions

The use of intelligent tools to predict the lead time process is essential to be discussed in new researches. In academic literature there are few scientific research using data mining and ML to lead time prediction and analysis. Faced with the common manufacturing planning methods, ML techniques can be efficiently used to predict the lead time process in the Industry 4.0 and are a viable solution for data analyze, autonomously management, predict information and optimize the process and services. Integrate technologies in Industry 4.0 generates a lot of information and this needs to be a process, extract useful knowledge to help management in real-time into smart factories. Furthermore, ML techniques applied in management process has relevant advantages, such as understand the data patterns, behaviors, learn and understand news insights of past historical data, makes possible automatic decision-making machine-to-machine within the production systems, and consequently increase the assurance of prediction and decision making in industrial process. Also, the ML applied in the lead time process can be used to reduce the problems in production scheduling, delay of product delivers, lack of stock, errors in production optimization problems and increase the industry credibility. However, there is still future research that should be investigated.

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