Industry 4.0: why machine learning matters?

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Abstract

Machine Learning is at the forefront of the Industry 4.0 revolution. Both the amount and complexity of data generated by sensors make interpretation and ingestion of data beyond human capability. It is impossible for engineers to optimise an extremely complex production line and to understand which unit or machine is responsible for quality or productivity degradation! It is extremely difficult for engineers to process monitoring or inspection data as it requires a protocol, a trained and certified engineer as well as experience! It is extremely difficult to guarantee the quality of every single product particularly at high production rates! Artificial Intelligence can help answering the above questions. Indeed, Machine learning can be used for predictive or condition-based maintenance. Even without knowing the design of the machine (i.e. gearbox stages, bearing design, etc), a machine learning algorithm is capable to monitor deviation of monitoring sensors features compared to a healthy state. Machine learning can be used to monitor the quality of production by allowing the automation of the quality control process. Monitoring additive manufacturing process to detect defects during printing and allow mitigation through real-time machining and reprinting of the defective area. Ensuring the quality of very complex and sensitive production processes such as MEMS, electronic wafers, solar cells or OLED screens. Brunel Innovation Centre is working on developing algorithms combining statistical, signal/image processing for features extraction and deep learning for Automated Defect Recognition for quality control and for predictive maintenance. Brunel Innovation Centre is also working on integrating those technologies into the Digital Twin.

Keywords: Industry 4.0, Machine Learning, Digital Twin, In-line Inspection

1 Introduction

The term industrial revolution was first popularized by the English economic historian Arnold Toynbee to describe the process that led to United Kingdom economic and industrial development from 1760 to 1840. Steam power and mechanised production are among the most recognisable developments associated with the 1st industrial revolution but the 1st revolution has various features technological, socioeconomic and cultural. Among the technological changes, the use of new materials (iron), the use of new energy sources (coal, steam), the invention of new machines (spinning jenny), a novel organisation of work in the factory system, development of transportation and communication and the increasing application of science to the industry. The 2nd industrial revolution (1870-1910) also referred to as the technological revolution is considered the basis of modern life paving the way for widespread electricity, modern transport, water supply and sewage systems, etc. This has been achieved through major advances such as petrol replacing coal as the main energy source and the discovery of the

Bessemer process for the mass-production of steel but also the electrification, the invention of the internal combustion engine. The increase of the size of industries resulted in complex production, maintenance and financial problems that led to significant developments in industrial engineering, manufacturing engineering and business management. Such developments have been pioneered by Frederick Winslow Taylor leading to the theory bearing his name [1] and Henry Ford [2] optimisation of factories for mass production of standardised products. This was achieved thanks to precise and organised moving assembly lines using purpose-built machines simplifying the production and allowing the employment of unskilled workers. The 3rd industrial revolution (1950 to 1980) is the digital revolution and built on the development of semiconductors, transistors and microprocessors. This led to a progressive move from analogue to digital electronics in the industry. The development of programmable logic controllers, PID Controllers, computers and network communication resulted in control systems such as SCADA and allowed a progressive automation of production and the centralisation of monitoring and control of equipment, machines, processes and production.

Industry 4.0 or the 4th industrial revolution is a revolution in the making targeting smart and flexible manufacturing with mass customization, better quality and improved productivity. This paper is organised in 3 sections; the 1st presents Industry 4.0, the 2nd explains why machine learning is needed for industry 4.0 and the final section presents examples of work developed by Brunel Innovation Centre (BIC) in the context of Industry 4.0

2 Industry 4.0

Industry 4.0 is a strategic German initiative. The final report of the working group [3]. It is easier to understand Industry 4.0 through its five main objectives:

- *production flexibility* by optimising the steps in a manufacturing process in order to reduce cost, optimise machine loads and reduce dead time.
- *convertible factories:* that generate individualized products which requires a modular factory that adapts near real time to customer specific and different requirements while achieving mass and low-cost production
- *customer-oriented solutions:* by using sensor data to understand better the customer environment and need and adapt the product or service accordingly
- *optimised logistics:* by linking customer orders to predictive algorithms assessing consumables and material required and by optimising the supplier choice on the delivery route to achieve both an optimised cost and respected deadlines
- *use of data:* data was already available thanks to the 3rd industrial revolution but it is local and the SCADA standard widely used is very rigid and not suitable for production flexibility and

convertible factories. In the context of industry 4.0, the production data can be used more intelligently for monitoring the process efficiency, cost, health and reliability but also for monitoring the product during its life opening up opportunities for new business model (service rather than product or both)

- *circular economy:* the availability of data during a product life allows assessing the life of a product and planning recycling as well

The Industry 4.0 is an outcome of the current digital era but where the 3rd industrial revolution was driven by digital electronics, the 4th revolution is driven by Internet. Indeed, the connectivity is key to Industry 4.0 and by connectivity we mean the intra-connectivity which was achieved in the 3rd revolution but lacked flexibility. More importantly, by connectivity we mean the vertical connectivity with the supply chain and the customers and the horizontal connectivity between production, maintenance, logistics, research, marketing and finance. The near real-time flow of data between different departments and different stakeholders is the key to achieving the above objectives.

In practice, Industry 4.0 is achieved by mapping continuously the physical events during production and service to the digital domain. C. Paolo et al [4] lists the key enabling technologies for Industry 4.0 as shown in Figure 1.

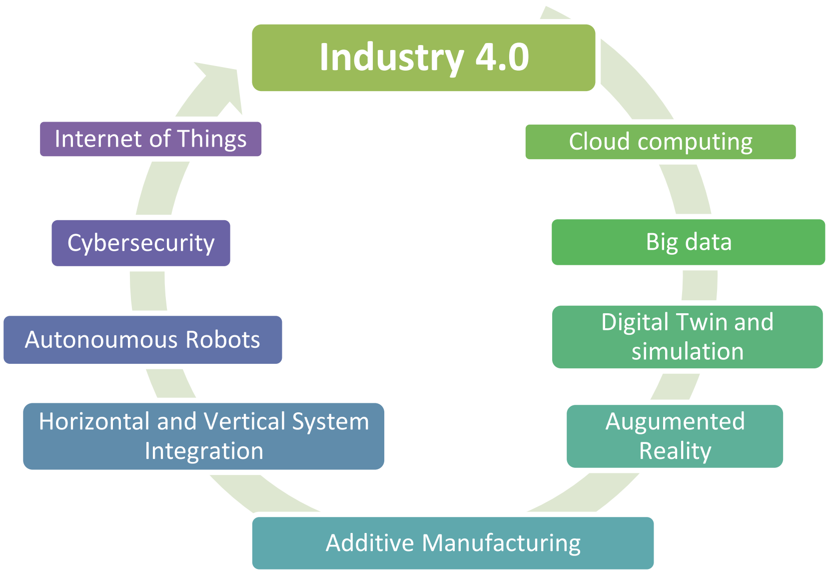

Figure 1 Enabling technologies of Industry 4.0 [4]

2 Why machine learning matters?

Industry 4.0 is built upon connectivity and data. The data is coming from the production units, from the machines, from the supply chain, from the logistics, from the intelligent and connected products, etc.

The reason such amount of data is collected is to support manufacturing, maintenance, industrial planning and business intelligence. Wang et Al [5] states that manufacturing systems should be able to monitor physical processes and make smart decisions through real time communication with humans, machines and sensors. The processing of the potential huge amount of data and the smart decision making requires machine learning as humans are unable to process either complex or huge amount of data. Through a training process, machine learning algorithms are capable of creating virtual models of a production line, a factory or a process and use link the materials, power and consumables, the production steps and time and the output no matter how complex it is. The trained models allow optimising the production depending on customer specific requirements and delivery times and optimise the production to minimise cost, respect deadlines while guaranteeing quality. The machine learning algorithms can automatically predict required consumables and materials and inform the supply chain as well as optimise the logistics for both cost and guaranteed on-time delivery. The trained algorithms could handle partially or totally all the above operations depending on the quality and reliability of the data coming from different stakeholders. They can also provide scenarios to human to make the final decisions.

Machine learning algorithms can be used to monitor – without extra-sensors -the health of the process and the production by evaluating deviations in power or time of production of the whole process as well as individual machines and alert on deterioration and risk of failure. If the production process is equipped with relevant sensors for condition monitoring of machinery or/and quality control of the product at different stages, they can be used to monitor in real-time both the quality of the products and the health of the machines allowing a high degree of certainty about the productivity, the efficiency, the health and the quality of the production units.

3 Case studies of machine learning in Industry 4.0

In the context of Industry 4.0, BIC work focuses on developing machine learning algorithms for condition monitoring, structural health monitoring and in-line inspection. In this section, we review the impact of machine learning on various industry 4.0 areas emphasizing BIC developments

3.1 Machine Learning in Additive Manufacturing

Additive manufacturing is a key technology for industry 4.0 as it allows production flexibility and customer-oriented solutions. Defects that occur during the additive manufacturing (AM) process can result in irreversible damage and structural failure of the object after its manufacturing [6]. Machine learning can be implemented in AM process to achieve high quality products. ML can be implemented as an additional layer to the real-time and in-situ Non Destructive Testing (NDT) evaluations. The nature of some AM methods means that not all NDT techniques are effective in characterizing critical defects [6]. Thermography, X-ray computed tomography (CT scan), or digital radiography are limited by the resolution of images and cost and are not ideal for real time monitoring [6]. Beyond defect identification and quality control, ML could be applied in additive manufacturing for process parameter optimisation, process monitoring and control. Collins et. al, [7] reported a machine learning model capable of predicting and estimating mechanical strength of a part manufactured using Electron Beam direct Manufacturing. The model was able to identify distribution of yield strength using deep learning and genetic algorithms (GA). For Metal Arc welding, Xiong et al. [8] have proposed a deep learning model to optimize the bead geometry based on several process parameters such as feed rate, speed of welding, arc voltage and nozzle to plate distance. BIC is developing in the EM-ReSt project [6], Electromagnetic Acoustic Transducers (EMAT) and Eddy Current Transducers (ECT) for real time monitoring of AM components. Big data collection and analysis will be performed and blended with statistical, machine learning and big data analysis for the estimation of the likelihood of AM techniques to introduce anomalies into the printed structures.

3.2 Machine Learning in Digital Twin

Digital Twin is a digital representation of a physical system developed independently and connected to the physical asset. The digital information could include multiphysics based physics model of the asset or sensory information. According to Glaessgen and Stargel [9]: "*the digital twin is an integrated multi-physics, multi-scale, probabilistic simulation of a complex product and uses the best available physical models, sensor updates, etc., to mirror the life of its corresponding twin.*". Multiple researchers have empirically and theoretically proven that machine learning and big data technologies have improved the efficiency of production. Techniques such as data mining, pattern recognition and deep learning have a been demonstrated [10-12]. However, actual and real-world applications and reported case studies of ML in manufacturing are very limited [13]. ML and big data are being utilized in manufacturing domains such as: Value creation [14], and Quality control [15]. For tackling uncertainties in manufacturing, Monostori [16] reported a hybrid AI and multi-strategy machine learning approach.

Machine learning can be implemented in all the above listed manufacturing domains. Qingfei et al. [13] proposed a Machine Learning based Digital Twin framework as shown in Figure 2. This framework aims to optimize production in petrochemical industries. Similar models can be implemented in other industries to improve the production efficiency.

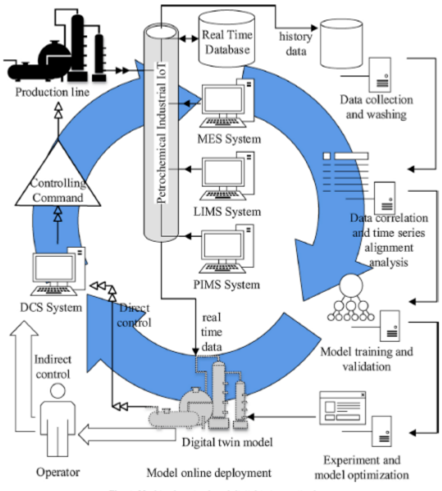

Figure 2: Machine Learning based Digital Twin framework [13]

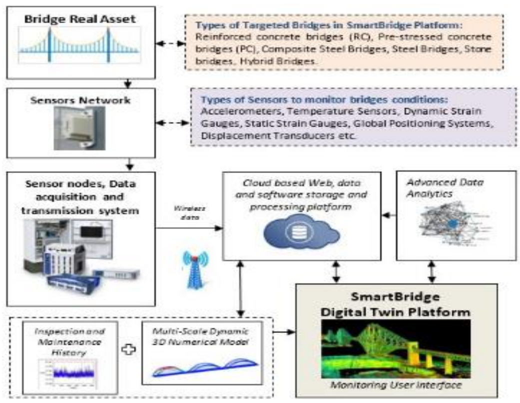

Figure 3: Project Smart Bridge Concept [18]

BIC is involved in collaborative research projects aiming at developing a digital twin of a wind turbine and a bridge. *WindTwin* [17] aims to create a virtual copy of a wind turbine. The digital twin of the asset aims to improve the understanding of performance variations, anticipate wear and failures and implement condition-based maintenance instead of planned scheduled maintenance. The project is developing modelica models of the machinery and application of machine learning for enhancing condition monitoring algorithms and improving defect detection. Smart Bridge **Error! Reference source not found.** aims to create a virtual model of a railway bridge located near London. The virtual model developed allows monitoring the condition and degradation of the asset combining data from IoT sensors and Artificial Intelligence algorithms considering environmental, operational and historic conditions. The project also aims developing risk-based inspection algorithms based on the monitoring data and loading of the bridge.

4. Conclusion and perspectives

Industry 4.0 and its enabling technologies are a very dynamic area of interest for the industry and the academia. A lot of resources are being invested in developing the enabling technologies: IIoT, clould computing, machine learning models and libraries, etc. The Industry 4.0 still suffers from the limitations of any young concept *the lack of standards*. Indeed, there is no communication protocol for industry 4.0, no security standards and not even a standard definition of Industry 4.0

According to Annalise Suzuki, Director of Technology and Engagement, at Elysium Inc, there is no standard for machine to machine communication which is a key to Industry 4.0 implementation. The development of standards for Industry 4.0 is particularly challenging given that this revolution aims to connect not only the whole supply chain but the whole stakeholders which makes agreements more challenging to achieve.

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