Machine Learning In Manufacturing

A survey on trends and applications of Machine Learning in the Industrial Automation

Lavish Thomas
Department of Computing
Letterkenny Institute of Technology
Donegal, Ireland

***Abstract*— This review paper provides an analysis of the current state of Machine Learning in the field of Manufacturing Industry. It gives an introduction to the manufacturing domain, presents various segments of the industry, a brief history of industrial revolutions, the current state of the Machine Learning research and development in the industry. Some widely used algorithms and techniques are discussed on the basis of relevance, efficiency and popularity. The paper discusses the current trends in the manufacturing industry and developments happening in the various segments of the industry. A categorization of current challenges in this new age of manufacturing industry is also presented in order to illustrate the maturity level of each vertical of the industrial automation domain.**

Keywords—machine learning, manufacturing, industry 4.0

I. Introduction

This paper will study the current trends of the manufacturing domain and analyse the applications of Machine Learning in industrial automation. A brief introduction to the manufacturing domain and history will be discussed in order to set the context. Furthermore, trends in the manufacturing domain with respect to machine learning will be discussed. Various applications and generally used algorithms for the same will be presented. Finally, challenges faced in the current implementation of ML and issues which may occur in future as the industrial automation technologies advances will also be discussed.

II. Industrial Automation

A. Importance of the Manufacturing industry

The maturity level of industries has been always a key indicator of any nation's development status. As history teaches us, starting from the medieval period always nations with best industries has flourished. Even in the first and second world war, the roles industries played was enormous. Countries had invested heavily in the industries, majorly on military equipment productions. This had led to a huge scope of research and development in the industry, especially in times of the cold war which had given a boost to scientific research on technology and its realization via industrial revolutions.

B. Industrial revolutions 1.0 to 4.0.

Currently, industry 4.0 has been a buzz word around the manufacturing industry. The term is based upon the by German Government's strategy [1] to promote computerization of manufacturing. This is based upon three previous revolutionary stages of industry automation. First industry revolution, which happened around late 18th century and early 19th century, consolidates the transformation from hand-based work to more mechanics-based methods of work, usage of water, steam-powered machines, and the inclusion of chemical processes to increase the quality and quantity of the products. The second industrial revolution which represents the introduction of electricity and telecommunications systems happened between late 19th century and first world war in 1914. The invention of PLC's in the late 1960s by Bedford Associates and the rapid development of computer communication systems led to the third industrial revolution [2] and remains as the core of current industrial automation projects.

C. Basic Components and architecture

From the third industrial revolution, the industry is dominated by PLC (Programmable Control Logic) based control systems. PLC is a specialized computer in RISC (Reduced Instruction Set Computer) architecture which is highly reliable and accurate. There are 3 elementary blocks of an automation system in the industry as illustrated in Fig. 1. The Sensor provides the PLC with current process value (e.g. Current temperature), based on this value and programmed logic the PLC takes a decision about the value which has to be passed on to the actuators such as motors (e.g. rpm).

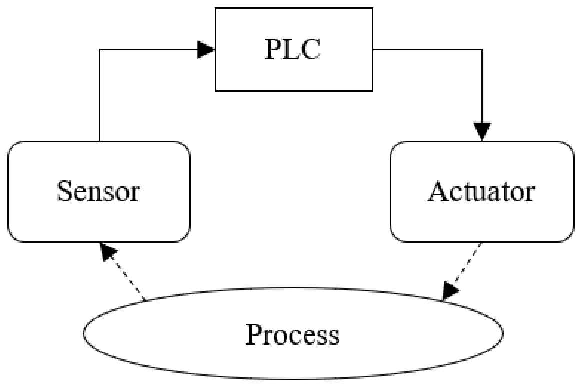

Fig. 1. Interaction of sensors, actuator and PLC.

The automation pyramid which is illustrated in Fig. 2 represents the data flow in the industry. Data gets aggregated when it is moved from one layer to another. How this affects the implementation of Machine Learning Models is later discussed in the decision support algorithms. The levels are a mechanism of reducing the amount of data flowing, and to bring meaningful insights to the plant management. This also segregates the functions in a horizontal way in order to have specific standards and protocols which creates openness in the manufacturing domain.

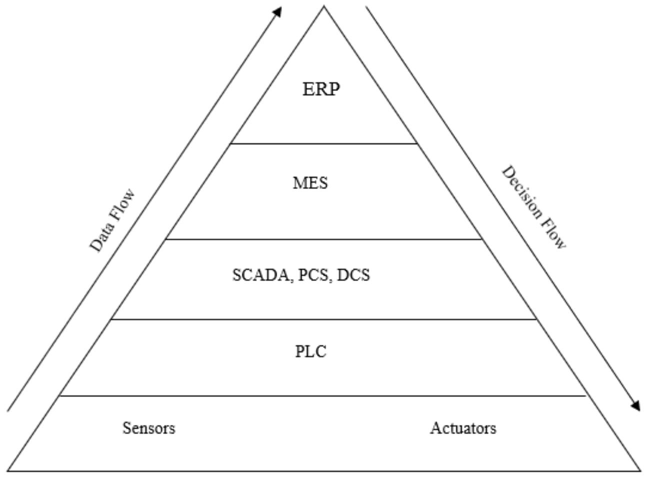

Fig. 2. Automation pyramid.

D. Categories

The manufacturing industry is majorly categorized into two sectors, process industries (continuous process) and digital factories (discrete signal-based applications in factories). Because of the sensitive nature of data and critical system in the process industry, it is not conventional to adopt new technologies swiftly. For e.g. ML and AI methodologies in the current context. This category of plants and projects are conservative in terms of incorporating new technologies. Whereas in digital factories, it is comparatively easy to adapt and implement.

The discrete industry can be considered as one of the first adaptors of machine learning techniques in implementation as some of the current routing and batch processing applications are based out of machine learning, and have been in the production from early years of this decade. A good example is GE Predix [3]; other technologies companies like Microsoft, Amazon and Google are trying to get into the domain with their cloud-based IoT services to integrate the data analytics and ML platforms of their own.

III. Trend Analysis

When Artificial Intelligence was getting traction in the early '80s, the manufacturing industry tried to embrace these new methods and the extensive study was done on the same. But due to the lack of technology available at the time, the interest on the topic was deteriorated in the industry domain. But once again from mid of this decade, the AI and ML topics are gaining attention from several businesses in the manufacturing [4]. According to the paper by Sharp et al. [4] in journals published in recent years, there is a great increase in ML and AI-based papers in the manufacturing industry. They also provide evidence to show that the ML applications are still server-centric, and there is an unventured scope in app-based applications.

Another reason for the growth of ML in manufacturing is an advancement in computing and cloud technologies [5], expansion of IoT (internet of things) and increased use of cyber-physical systems [1]. The industry is also looking for solutions to provide some level of custom manufacturing, where manufacturing setup can be flexible enough to produce tailor-made for user-specific sizes and selective features. This is a major milestone which the companies are working towards; an initial version of this service for customers are available now. But these systems use existing ERP and MES systems in a conventional programmed way. An automated way to suggest the user for the custom products and optimizing the process over the course of time is what it is expected of AI and ML technologies in this area from the manufacturers[6].

Usage of machine learning in various functions of manufacturing [7] is illustrated in Fig. 3. As per Ge, the main usage is the control functions, followed by optimization and monitoring. Performance assessment, prediction, oscillation detection segments are also using the ML techniques but in a limited way.

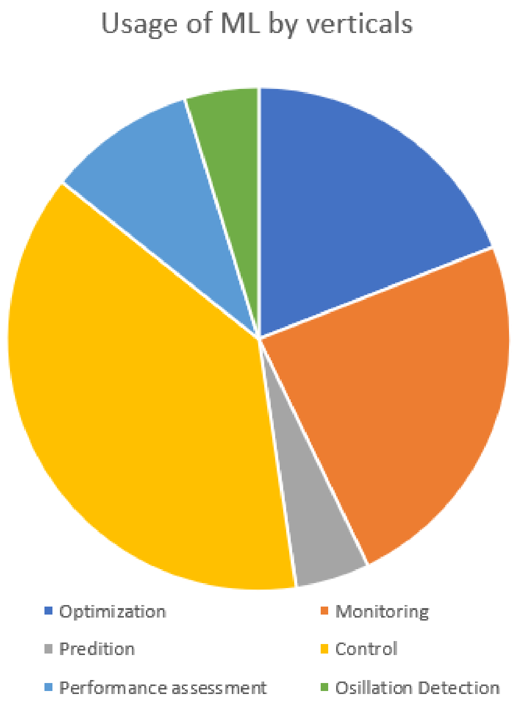

Fig. 3. Distribution of the usage of ML applications in industry functions [7]

IV. Areas of Applications

The areas of ML applications in industry various from supervised learning to deep learning. Based on the area of applications various algorithms have been suggested in various forums. The algorithms with the self-updating feature using the new incoming data (experience) are one of the most prominent techniques used in Industry Systems [4].

The reason why machine learning is getting popular is the introduction of distributed control systems which have high-quality data collection capabilities, along with the advancement of transmitter technologies in the process industry[7]. Data mining and Databases are the solutions which were conventionally used in the industry to derive performance indicators, process monitoring etc, this has paved an easy way for ML technologies as the same can be done in a more automated and insightful way.

Ge[7] has also proposed an ideal way of data flow in smart manufacturing. As illustrated in Fig. 4, the plant is divided into several blocks of functional components, into order to simplify the massive scale and complexity of the plant-wide management strategy. The steps of designing the program are divided into several blocks of process decomposition, data pre-processing, sample and variable collection, model selection and training and process monitoring[7].

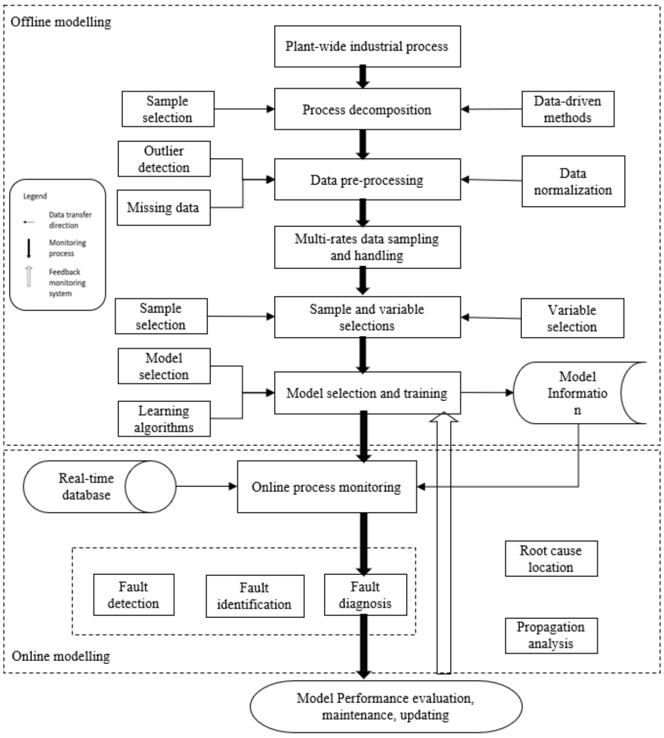

Fig. 4 Data flow model proposal of the ML-based manufacturing plant by Ge [7].

As described earlier, the applications in industry are diverse in nature. Based on the segments and user profiles, applications of ML in the manufacturing industry can be broadly classified into:

A. Control Functions and Decision Making

The estimation of a plant installation cost and operating cost has always been a complicated procedure in which input from various sources have to be considered and multiple actors have an impact on the same. Some of the most widely used techniques in decision making are Back Propagation Neural Networks [8] and Genetic Algorithms [9]. In the former method, Backpropagation neural network is merged with Least Square Support vector machines to achieve life-cycle cost estimation problem [9], this makes use of databases with features and samples [10].

Genetic Algorithms tries to answer more complex questions where decisions have to be made with loosely defined criteria and a few elemental heuristics to work with. This method is highly useful when the systems have more moving parts and actions of external factors have a higher influence on the outcome. A similar method was proposed by Yusof et al. [11] for the efficient usage of machines in the industry where Flexible Manufacturing Systems (FMS) are in place. The method considers the problem statement as ‘allocation of part operations and tool to the machines’ and ‘optimization of the objective(s) subject’. This technique is used for maximization of throughput, maximization of the utilization of resources, and minimization of processing and tooling costs [11]. But a drawback of this method is that it increases the mathematical and computational complexity because of the increased number of dimensions. To overcome this, harmony search (HS) algorithm[12] is suggested by Geem et al. in which a blend of heuristic factors and reduced dimensions is used; advantage of this solution is that, by reducing the design and development of the plant and its operations, it still holds an accuracy level close to the fully informed decisions which were costly to use.

B. Maintenance

Another important application of ML comes into the maintenance of the machine parts in the industry. In early times, the plant will be kept running till a breakdown happens (Reactive maintenance) [4], this causes an unprecedented halt of the manufacturing process and longer downtimes as the part replacement and re-initializing the process would take time. This may even cause cascading failures in other machine parts. A conventional solution for this problem was maintenance cycles, where activities like part-replacements, lubrication was done based on some predictive maintenance methods. There are basically three categories of predictive maintenance which have been developed over time [4], those are:

1) Cycle-based maintenance:

The maintenance for the plant is done after a specific time of running based on empirical calculations, for e.g. if we know the viscosity of the oil reaches the threshold in 3 months, the oil change is scheduled for every 3 months.

2) Current condition-based:

An evaluation is done on the current state of the plant and if the lifetime is near to the end or when a predefined condition is met, maintenance is the scheduled.

3) Predictive maintenance:

This is an improvement of the second method; based on the previous data of failures and technical specifications of the machines, approximate time of break down is estimated and preventive maintenance is scheduled. This method is also used in predicting the “Remaining Useful Time” [4] which in turn is used in inventory management to procure the replacement parts in advance to reduce interruption to the plant operation.

The machine learning methods are applied to the first category when maintenance has to be scheduled for the entire plant. In the second category, the role of ML is less compared to the other two because of the historic data of this method are comparatively less and irrelevant. Major use cases for ML appears in the third category. The machine learning techniques such as linear regression is widely used in the third category of maintenance when it is specific to a machine or large component of the plant where predictions are done based on the dataset of the past.

Wu et al.[13] have developed a method which can predict the RUT of rotating types of equipment. This technique makes use of ML and Neural networks, and derive optimal maintenance strategies for the equipment. When unnecessary maintenance cycles are reduced and breakdown time is predicted, the cost of running the plant is optimized to a greater extent.

Paolanti et al.[14] have proposed a method of predicting the maintenance time for electric motors using Random Forest approach. The approach deals with two types of forecasting methods: 1) Cross-sectional: where the critical condition of the parts involved in the system is calculated by comparing process values of the current state and threshold value derived based on past data. 2) Time-series: The algorithm predicts the future value and estimates an approximate time where the system will reach a critical state.

C. Monitoring and Knowledge Management

The amount of data is huge in the industry for the usual data representation systems (like RDMS) to handle and conventional programming is not enough to cover all the scenarios as the form in which the data is generated and collected are not apt for the traditional algorithms. Derivation of the logics will be mostly by manual study and interpretation of the data available, which time-consuming. This is where the importance of ML is highlighted. ML programs help to reduce the complexity of data and to do aggregation of data based on the correlation and relations (dimensionality reduction).

Choo et al. [15] mention a hierarchal system for the diagnostic analysis and a preventive prognostic. This is like the V-model of normal software development, there are a corresponding aggregator and segregator programs running at each level (each stage of development as a corresponding checkpoint in testing). Aggregation of data is done upwards in the automation pyramid to derive the high-level knowledge and management of data. Then afterwards, based on the high-level insights, a reverse propagation of the insights is done through each level until it reaches the basic elements in the production line. This method claims to reduce the exponential complexity of centralized data management systems.

A method of data analytics for robotic arms is suggested by Gerald et al. [16] which integrates Linear Temporal Logic with their control schema. As per the author, the method could be used in future to reduce the wear and tear of the joints by optimizing the movements for a job given to the robotic arm.

D. Cyber-Security:

As the industry is getting smarter and more connected, the security of the industry is also getting challenging. The attacks on the industry are evolving. Smart devices with wireless and ethernet connection capabilities were not part of the previous security frameworks for the industry. Thus, an evolving security system is the need of the industry. Wickramasinghe et al. [17] have suggested a deep-learning-based regularization method for cyber-physical systems. This method makes use of existing techniques like malware mitigation, anomaly detection, access control and intrusion detection in security domain in order to learn how new attacks can be prevented and provide an autopatch in case a security breach happens.

V. CHALLENGES

The industry domain is undergoing drastic change due to the fourth industrial revolution. The adaption of new technologies is no longer seen with scepticism. But the conservative behaviour of the industry demands the technologies to be reliable, resilient and robust. Challenges can be broadly classified into four:

A. Coupling of elements and functions:

The ML programs majorly work based on data, but in field-level, the data is explicit to the specific functions. These isolated set of data is rarely of any use to Machine learning algorithms as a correlation between elements cannot be derived. Due to the very low bandwidth, conventionally a very small sub-set of actual data is collected; this again reduces the efficiency of ML programs [18]. Solutions using IoT and Edge Gateway applications are developed to address these issues. There is an attempt to run the ML model on these gateway applications as a part of Edge analytics framework.

B. Latency:

Most of the current ML applications are implemented using a cloud-based or a server-centric framework. This is fine in terms of data analytics applications of ML, but this introduces the challenge of latency into the decision-making algorithms. The decision is very crucial in the process industry, a delay in this can cause substantial errors in the process staging and lead to damages in millions of euros.

C. Accountability and Responsibilities:

As the industry to moving to a smarter way of manufacturing with almost no human interaction, there is an ethical question of responsibilities and accountability. When liability is created due to an error in the ML program, who should bear the same; the owner of the manufacturing unit or the plant engineering company who deploys ML programs. A strong legal framework needs to be established in this vertical in order to bring sustainability.

D. Smart devices and cyber-physical systems:

The new industrial types of equipment are smarter in terms of processing power and communication systems. This opens up a new front of vulnerability in terms of cyber-security. The devices are getting smarter from bottom-up in automation pyramid, whereas the previous generation used field protocols like HART, Mod-bus etc. Currently, new devices come with wireless and ethernet connectivity. Even though these are advantageous technology advancements, the scaling up of security measures is demanded by the industry.

VI. CONCLUSIONS

Machine learning once again is gaining popularity in the manufacturing industry. The previous discarded and halted works of ML in the manufacturing industry is being revisited and taken-out of archives in this AI spring. Two major sectors which are popular in machine learning application in the industry are preventive maintenance and decision automation. The increase in the usage of high-level network protocols has enabled better features and accessibility to ML software. Another aspect of the ML applications is the smart devices and edge analytics gateway, which can also deploy machine learning models in order to reduce bandwidth usage and latency. Certainly, increased network activities call for increased security measures for the industry because of the value at stake accounts to millions of Euros. Even though a lot of groundwork has been done for ML in the manufacturing industry, real applications have a lot of scopes to expand. To conclude, cost reduction in manufacturing is expected by the implementation of Machine Learning Technology which will, in turn, will reduce the cost of manufactured goods for the end customers.

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