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Towards smart manufacturing: Implementation and benefits

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Abstract

Production activities is generating a large amount of data in different types (i.e., text, images), that is not well exploited. This data can be translated easily to knowledge that can help to predict all the risks that can impact the business, solve problems, promote efficiency of the manufacture to the maximum, make the production more flexible and improving the quality of making smart decisions, however, implementing the Smart Manufacturing(SM) concept provides this opportunity supported by the new generation of the technologies. Internet Of Things (IoT) for more connectivity and getting data in real time, Big Data to store the huge volume of data and Deep Learning algorithms(DL) to learn from the historical and real time data to generate knowledge, that can be used, predict all the risks, problem solving, and better decision-making.
In this paper, we will introduce SM and the main technologies to success the implementation, the benefits, and the challenges.

Keywords: *Smart Manufacturing (SM), Industry 4.0, Internet Of Things (IoT), Artificial Intelligence (AI), Machine Learning (ML), Deep Learning (DL).*

1. Introduction

With the technology advancement in recent years, there have been great advances in industrial domain that allow the introduction of the fourth industrial revolution (Industry 4.0) and specifically the move towards smart Manufacturing (SM). that refers to the application of the most advanced Information and Digital Technologies (IDT), such as Internet of Thing (IoT) supported by wired or wireless networks, cloud computing, big data [1], and artificial intelligence (AI) technologies, moreover, these technologies enabled the fusion of physical and virtual worlds through cyber-physical systems (CPS) [2], to achieve more efficient by producing with higher quality and lower costs.

As opposed to traditional factories and in order to increase manufacturing productivity it is necessary to develop an intelligent systems and strategies[3] with the help of network and data, that allow to make better-decisions in the right time, through collecting The physical data at different stages of product's cycle life, by extracting data from the machines that are fully connected and monitored by Industrial Internet of Thing (IIoT) such sensors, the RFID cards or bar codes used to identify products and production resources [4]. Further come the important role of AI technologies to analyse and understand the physical behaviour from generated data to control manufacturing activities, optimize physical processes, alert and predict risks in real time, and better decisions making.

The main purpose of this paper is to present benefits of the implementation of smart manufacturing for this, we segmented our study into three sets. Firstly, Maximum efficiency, which consists to boost the factory to the maximum agility and financial profitability. Secondly, proactivity which build up autonomous system that predict all the risks, and problems solving automatically. Thirdly, smart decision making which improves the decision making, by machine automatically or by helping decision makers to make smart actions.

This paper is organized according to the following sections: Section 2 details the literature review. Section 3 focused on smart manufacturing conversion and benefits from the implementation of SM, where we can go deeply on how succeed the implementation and the main keys of the SM. Section 4 focuses on the discussion of the results obtained. And, section 5 is devoted to the conclusion.

2. Literature review

2.1. Smart Manufactering (SM)

Several researchers defined the main keys to success SM. And bellow two examples, and in this document, we will use some of these technics to give a global model of SM.

• Shao, G., & Helu, M. (2020) set one of the most important keys to achieving SM: "Digital twin has the potential to be an important concept for achieving smart manufacturing", digital twin here means a CPS as cited in the same document. [23]

• Tao, F., Qi, Q., Liu, A., & Kusiak, A. (2018), defined the SM as a model of collecting data using IoT, and store it in a big data center then analyze it across big data technics and visualize it [20]

Traditionally Manufacturing was limited to a process or a sequence of process to convert a raw material (RM) to a finished good (FG) [8]. However, the SM comes to make manufacturing processes more and more smart and fully

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connected, benefited from various technologies and solutions, such cyber-physical production systems (CPPS), IoT, robotics/automation, big data analytics, cloud computing [6] and deep learning, with the aim of:

- Monitoring/Controlling and optimizing the production process in real-time by collecting the data at all levels of the supply network, be it on the shop floor, factory or supply chain[6] and then transforming all the raw data to knowledge to be able to better decision making based on predictive and preventive operations [7];
- Making the industry more efficient, profitable and sustainable;
- Exploiting the new and existing markets by producing complex and customized products [8] with high quality and low costs.

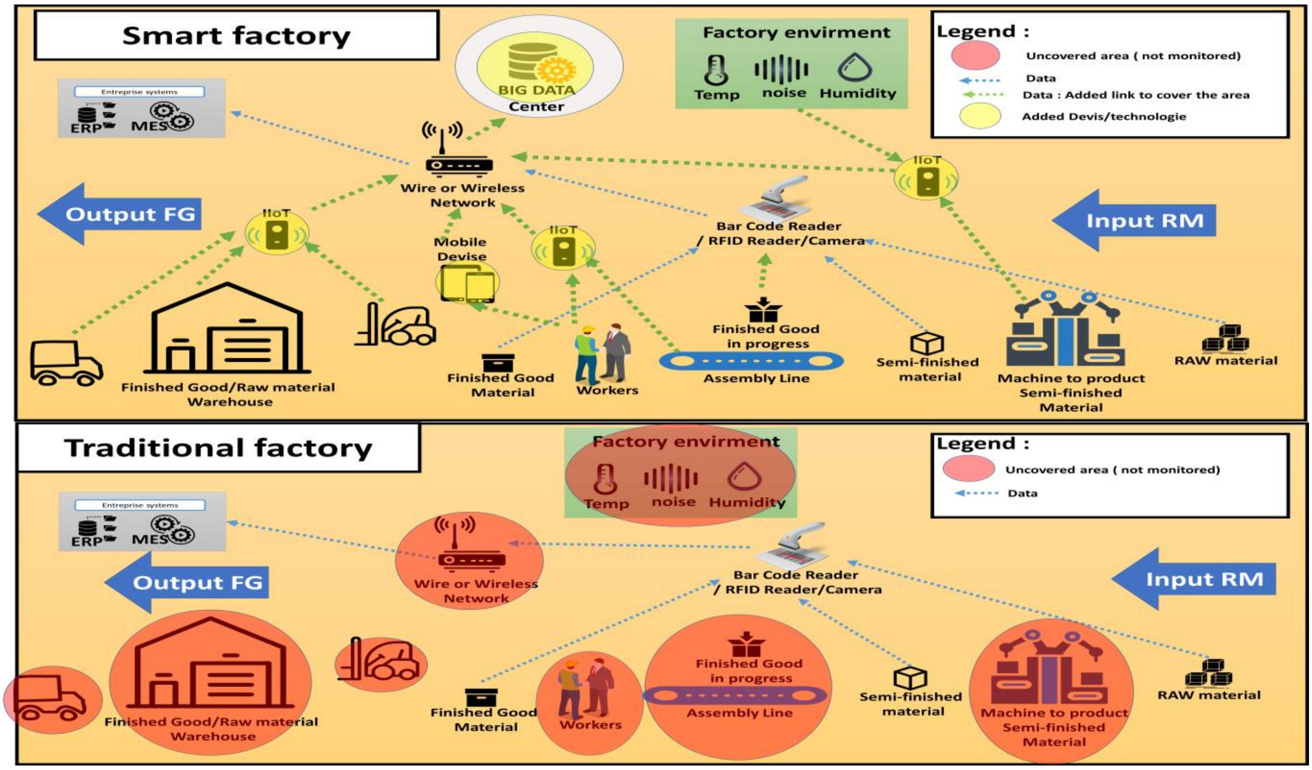

Fig. 1. Production line in a traditional factory VS Smart manufacturing.

Fig. 1 illustrates a topology of an standard industrial production line in a traditional factory, where a lot of areas are not covered by any system, the only focus is the input (RM) and the output (FG), the ERP/MES and standard systems are covering just the RM needs to order it from the supplier and generating the production orders to the shop floor to start the production. By implementing the SM, a new device appeared (i.e., IIoT, Sensors) and also technologies (i.e., Big data) to collect data from all the areas in the factory.

2.2. Internet of things (IoT)

IoT is one most keys to success SM. Yu, L., Nazir, B., & Wang, Y. (2020), defined IoT as “all kinds of sensors can exchange information with the Internet through wireless and wired communication methods” [24]. However, IoT is to collect data and connecting all the physical environment of manufacturing (i.e., Machines, Equipment, Products, Workers, Trucks) to the cyberspace of computing platforms. However During this revolution, Internet of Things (IoT) comes to cover this need by connecting the physical environment, collecting and sending the data in different types (i.e., Images, text, voice), and that’s lead to better decision-making algorithms usage and consequently forming a Cyber-Physical System (CPS). We name such industrial IoT dedicated to manufacturing industry as Industrial IoT (IIoT) that consists of a wide diversity of manufacturing equipment such sensors, actuators, controllers, RFID tags and smart meters, which are connected through wired or wireless network to the computing platforms. [15]

2.3. Machine learning (ML)

Machine learning (ML) is a branch of artificial intelligence (AI) that is using the historical data (experiences) to train computers to predict, generate solutions for complex problems, and minimize production costs and quality by early detection of production faults automatically and without explicitly developing the needed algorithms (Fig.2) [9,10,11], and the deployment doesn’t require long codes to be written due to vectorization, which allows the processing of arrays without using loops [11]. Since ML is using historical data as experiences the more, we have much correct data this can help to better and faster solving problems, however wrong data can lead to wrong results.

ML is a new concept where researchers are still working to take the advantages from using it in several domains, example of these researches:

• Chao Shang and Fengqi You (2019) [25], tried to demonstrate the advantages of using ML and analyzing the gap between practical requirements and the current research status.

ML is classified in three methods according to availability of the feedback (see Fig. 3):

• Supervised learning: the correct response is provided by a teacher;

• Reinforcement learning: less feedback is given, since not the proper action, but only an evaluation of the chosen action is given by the teacher;

• Unsupervised learning: no evaluation of the action is provided, since there is no teacher [12].

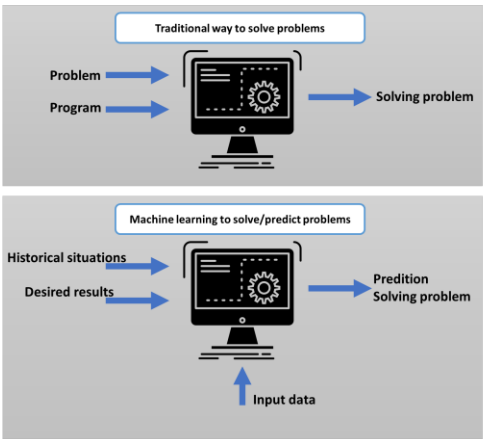

Fig. 2. Machine learning vs traditional way to solve problems

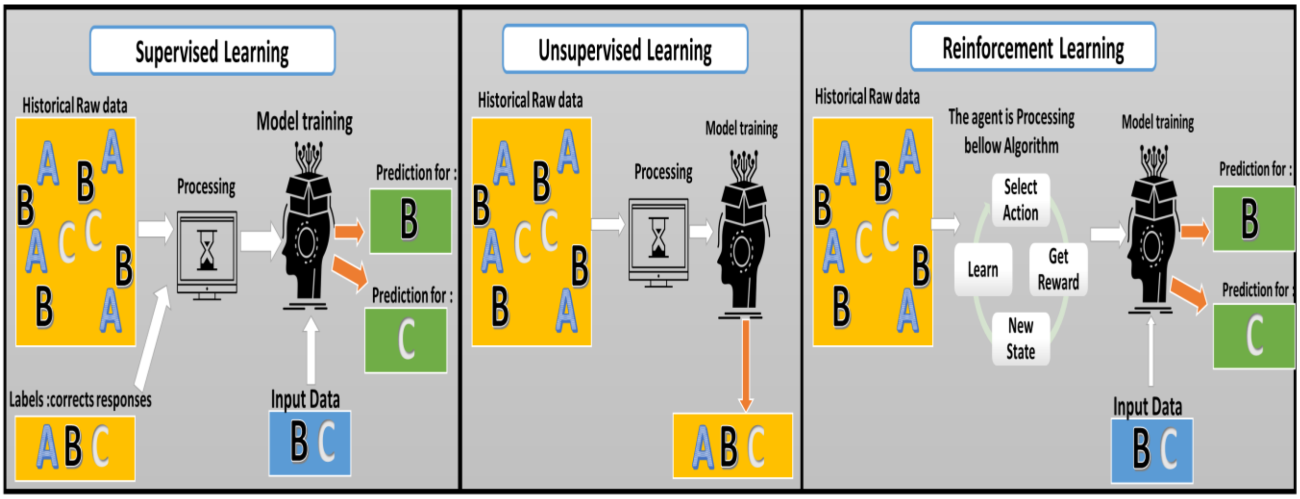

Fig. 3. Machine learning methods

It is important to state the fact that there is no single ML technique or algorithm optimal for all the problems in manufacturing. Every single use case can be analyzed separately and according to the requirements of the problem, the existing historical data (experiences) an appropriate machine learning technique has to be applied [10].One of the branches of ML is Deep learning (DL) that is using a set of algorithms based on the neural network concept, therefore, DL is simulating the neuron functionality to learn from historical data and apply to new data [11].

Some examples of using ML in manufacturing are:

• Managing and monitoring Tools/Machines/Equipment: Fault diagnosis and solve, Preventive maintenance, Predictive maintenance where is performed based on an estimate of the health status if a piece of equipment [13];

• Quality: identifying damaged products and predicting products quality drop and improve defect detections;

• Factory efficiency: Automatizing, monitoring and optimizing process, predicting downtimes to avoid it, minimize material wasting, better managing inventory by using smart scheduling, and predicting all the internal and external risks related the whole supply chain;

• Marketing: Predicting customers needs and all demand variations that can be done;

• R&D: Help in product configurations by identifying the potential risk factors and simulate the real word;

• Health and safety: Predict risks of accidents, that can impact workers or environment, especially in case of using dangerous equipment or products.

3. Towards Smart manufacturing and benefits

Recently, industrial sector is facing fierce competition, and the current industrial automation practices will achieve soon their limits. To deal with these facts factories are forced to move up to a smarter methods and technologies to be more flexibles, developing more complex products, predict risks and customer's needs, and reduce production costs. However, a new generation of technologies are developed that can help factories to deal with this competition, and to be smart manufacture.

SM is the digitization of the factory to start making better decisions, predicting customers needs, and all the risks that can impact the enterprise in terms of financial results, product quality, environment, the relationship with suppliers, customers and workers. In fact, the benefits associated with the implementation of implementing the SM can be resumed in three points: maximum efficiency, proactivity, and the Smart decision-making.

Fig. 4, illustrates a topology of, how the implementation of SM can be, by connecting all the factory's areas to a big data center, and start the exploitation of the data coming from this center and from the existing systems (i.e., ERP, MES), through deep learning algorithms. The factory's areas are divided in three sections:

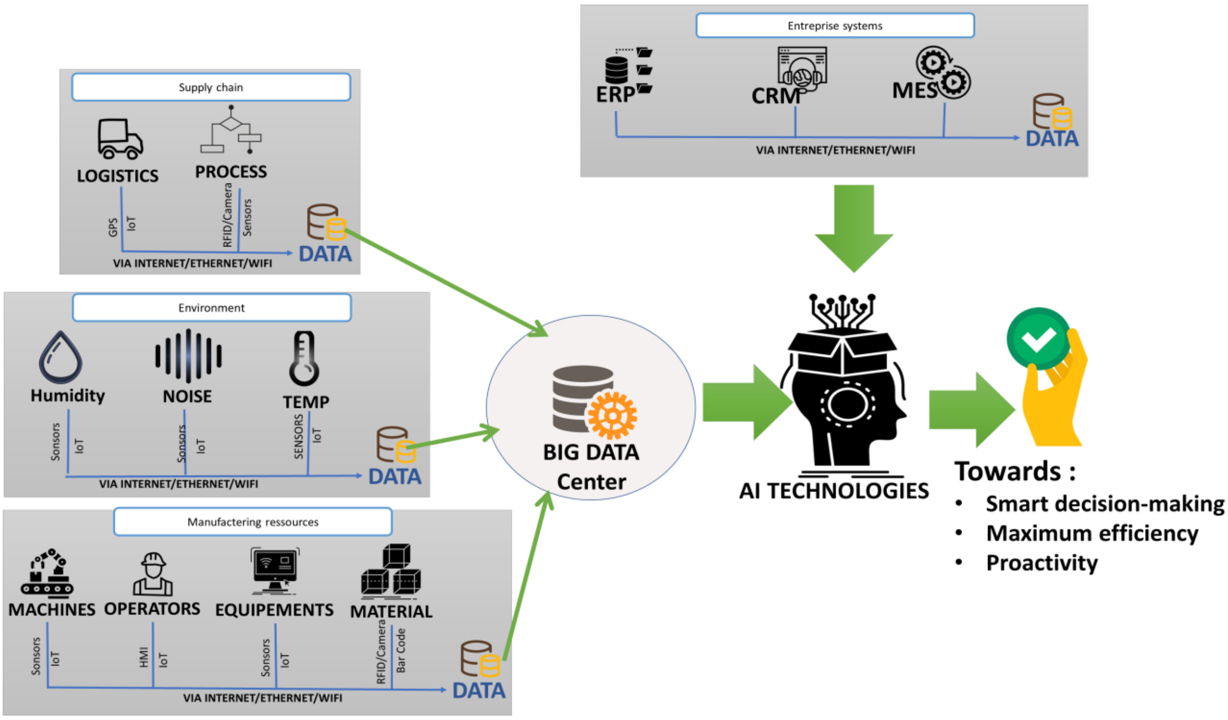

Fig. 4. Towards smart manufacturing

- Environment: Internal (temperature, noise, humidity) and external (weather);
- Manufacturing resources: all the machines, equipment (manufacturing and IT), humans and goods;
- Supply chain: external (smart transportation planning and means of transport that is linked with GPS) and internal (the process, smart logistics).

3.1. Implementing smart manufacturing

The main goal of smart manufacturing is to collect data in real time, analyze it in an automatic way, and use the results to improve the factory. Therefore, we can start by eliminating all hidden areas in the factory (Fig. 1.) through connecting all the tools, machines, equipment, workers, environment and supply chain to the cyberspace of computing platforms across IIoT technologies. Besides, Sensors, actuators, controllers, RFID tags and smart meters (IIoT equipment) that are connected through network, will generate a huge volume of different type of data. Traditional databases technologies cannot support this amount of data, as a result, we need to implement a Big data center, that will be the main data source to help the DL algorithms to learn by using it as historical data (experiences) to make the predictions to help better decisions-making. Hence, the implementation of the smart manufacturing need investment, the good news that the return of investment will be out paid, through the risks that will be avoided by predicting it, and the increasing of the production efficiency.

3.2. Maximum efficiency

There are two types of efficiency the first is technical which is producing maximum with a given set of inputs and technology. The second is allocative, defined as the ability to equate marginal value products with marginal costs [17]. The efficiency can be measured with three KPIs: Cost, Quality, Time, Flexibility [18]. SM is an opportunity to promote efficiency, by taking advantages of all the collected to data and the DL algorithms.

- Cost saving: Lower downtime, improve productivity, energy saving, improving supply chain by using smart logistics and SM (i.e., smart Transportation, optimize inventory levels and discrepancies, scrap reduction, obsoletes reduction), space optimization (by proposing layouts), reduce labor costs, reduce maintenance costs, minimizing the number of accidents and bad decisions;

- Quality: Without human intervention a SM can reduce the quality drop of production. DL algorithms also can help in developing new complex products with a higher quality;
- Time saving: Product process development (product's cycle time optimization), optimizing the changeovers, optimizing the fault diagnosis of machines and equipment;
- Flexibility: New product flexibility, demand variations.

3.3. Proactivity

- Enterprises are facing an ever-increasing turbulent and unpredictable business environment [1] that can lead to critical situations and huge financial impacts. To avoid this kind of situation, enterprises can use the past and the present to predict the future, by creating autonomous tools (i.e., self-learning, self-compare, self-predict, self-aware, and self-execution) based on DL algorithms and collected data from IIoT and other systems (i.e., ERP). These tools can diagnose root causes of the problems, recommend possible solutions, evaluate the operational and business impacts, and prevent similar problems in the future [19].

As a results, the autonomous tools can be proactive in terms of commercial forecast by modeling the markets and customers behavior and prices estimation, as they can be also proactive in terms of operations, by making a self-execution if necessary or sending early-warning/alerts of production abnormalities caused by equipment failure, lack of material, quality issue or operation deviation in advance whether and when production abnormalities will occur [20].

3.4. Smart decision-making

Making decisions in brief time is one of the hardest and yet most important tasks in the enterprise, therefore, the more we have targeted data and knowledge, the easier and faster we can take smart decisions, this assumption is valid for humans and machines (DL algorithms). Manufacturing data helps decision makers by making smart perception and smart analysis to improve the quality of decisions and making them more explicit, rational, efficient and the shortest possible time [5,21].

Manufacturing's decisions can be divided in two categories:

- Operational: Machine (DL algorithms) can take it in charge by taking self-decision and self-execution without human involvement, based on the knowledge taught by the self-learning done in the past and the predictions. Since the capacities of machines exceed human, the machine in this kind of situation can make smart decisions, except in some critical tasks that can request human validation;
- Managerial: SM allowed to systems and tools to be more linked with the physical, however, more realistic. By using the real-time data, the predictions and the scenarios provided by Machine (DL algorithms, Big Data), decision makers can easily make smart decisions. Moreover, the agility ensured by SM can also make the execution of the decision faster than traditional factory.

4. Discussion

This paper provides a model of implementing the SM, how to cover the traditional manufacturing to SM, and presents the benefits from implementing SM, were making smart decisions will be faster and easier, the efficiency of the manufacture can be boosted, and predicting risks can avoid crisis. Table 1 below shows a comparison of the main key characteristics between smart manufacturing and traditional manufacturing.

Table 1. Comparison between smart manufacturing and traditional manufacturing

Key	Traditional manufacturing	Smart manufacturing
Data	Not fully exploited, not total accessible	Real time data collection and visualization
Process and operations	Manual optimization	Automatically optimized, and full traceability
Downtime	unpredictable	Predictable
Maintenance	Preventive/Corrective	Preventive/Corrective/Predictive
Supply chain	Traditional	Smart and 100% transparency
Efficiency	Not fully exploited	Fully exploited
Product development	Time wasting and not flexible	Faster developed products even for complex products
Energy optimization	N/A	Yes
Quality	Manual inspection	Hight quality, less cost, automatic inspection
Flexibility	Not totally flexible	Totally flexible
Decision making	Poor data	Real time data, smart algorithm to prediction

As shown in the table, SM provides better results than traditional manufacturing. And provide the factory the ability to improve all the metrics, by giving the whole vision. And to better know the main discrepancies where to take corrective actions, moreover SM boosts to work on the future strategies and not just following the daily production.

Some challenges are facing the implementation of SM, the investment that can be a roadblock for the factories, but the return of investment will be out paid, through the benefits of SM. The security also can be sited as a challenge, but we can use some technics like blockchain with the aims to store and transmit data in a secure, more transparent, and decentralized way [22,26].

5. Conclusion

Smart manufacturing is a revolution of industrial domain and transforming a traditional manufacturing to a SM will be a necessity, especially in today's competitive market, where the main goal of customers is to obtain the best products with highest quality and lower cost. In fact, the more we are connected to the physical world via machines the easier and faster we can make better decisions, and the more factory's efficiency we have.

Converting a traditional factory to SM can be done in several steps, by elaborating a road map starting from connecting all the factory resources, then collecting data and visualize it, and finally implement deep machine algorithms to learn from the data and start the predictions and problems solving.

Deep learning changed the concept of a machine, from an algorithm's outlet that is executing just programs, to a thinker that is simulating the neuron by self-learning from the past experiences coming from several inputs and predict the future and solve complex problems.

This paper is representing the theoretical side of SM, studying practical and use cases can be a research challenge.

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