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An Industry 4.0 Vision With An Artificial Intelligence Techniques And Methods

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Abstract - The current industrial activity is rigid and difficult to change; innovations can hardly be afforded, reduction of raw material prices generally lowers quality and can increase process costs and, in consequence, profit margins decline constantly. All these inconvenient points to the need for the next great revolution in industrial manufacturing, which will lead to several enhance attributes in comparison with actual production activities for this new revolutionary industrial age an attribute thatis directly linked with artificial intelligence (AI). In fact, the defined cyber physical systems, connected by the internet of things, take all the attention when referring to the new industry 4.0. But, nevertheless, the new industrial environment will benefit from several tools and applications that complement the real formation of a smart, embedded system that is able to perform the autonomous tasks and most of these revolutionary concepts rest in the same background theory as artificial intelligence does, where the analysis and filtration of huge amounts of incoming information from different types of sensors, assist to the interpretation and suggestion of the most recommended course of action. For that reason, artificial intelligence science suit perfectly with the challenges that arise in the consolidation of the fourth industrial revolution. The aim of this paper is to present and facilitate the proposed Industrial AI ecosystem, which defines a sequential thinking strategy for needs, challenges, technologies and methodologies for developing transformative AI systems for industry.

Keywords: *Industry 4.0. Artificial Intelligence, Big Data, Embedded Systems, Internet of Things (IoT), Cyber Physical Systems (CPS), Radio Frequency Identification (RFID), Wireless Sensors Networks (WSN), Autonomous Robots.*

I. INTRODUCTION

The current industry has been changed to dynamic industry by the industrial revolution, so the manufacturers have been forced by the global market to reconsider their conventional manufacturing methods. The modern manufacturing requires and needs new manufacturing operations, procedures, and effective factory management has a great value in this area concern (S.S. Kamble et al., 2018).

Radio Frequency Identifier technology as a gadget of IoT (Internet of Things) has been utilized in modern manufacturing to enable the manufacturers to track and identify the objects or parts to get the required data. This procedures needs to equip objects with RFID tags and utilizes RFID antennas in certain places to enable readers to collect data of the objects. The calculation of mathematical model depends on the criteria such as the collision of these antennas, the coverage of network, and transmitted power in the network. The required number of antennas for RFID network lead to the concept of RFID Network Planning (RNP) optimizing. (R. Kuo et al., 2013). Implementation of the proposed hybrid artificial intelligence algorithm to solve and optimize the RNP has three phases which are defining working area which an RFID network should be established and optimized, defining the parameters of the proposed algorithm, and implementing the optimization algorithm todefined RFID network and evaluate the way of modelling and optimizing nonlinear RNP problems utilizing Artificial Intelligence (AI) techniques.(A. Azizi, (2017).

Artificial Intelligence (AI) is a cognitive science with rich research activities in the areas of image processing, natural language processing, robotics, machine learning etc. Historically, Machine Learning and AI have been perceived asblack-art techniques and there is often a lack of compelling evidence to convince industry that these techniques will work repeatedly and consistently with a return on investment (ROI). At the same time, the performance of machine learning algorithms is highly dependent on a developer's experience and preferences.

AI driven automation has yet to have a quantitatively major impact on productivity growth and present day industries are facing new challenges in terms of market demand and competition. They are in need of a radical change known as Industry 4.0. Integration of AI with recent emerging technologies such as Industrial Internet of Things (IIoT), Big Data Analytics, Cloud Computing and Cyber Physical Systems will enable operation of industries in a flexible, efficient. Since Industrial AI is in infancy stage, it is essential to clearly define its structure, methodologies and challenges asa framework for its implementation in industry. An Industrial

AI Ecosystem, which covers the essential elements in this space and provides a guideline for better understanding and implementation. (Jay Lee et al., 2018). Industrial AI is a systematic discipline, which focuses on developing, validating and deploying various machine learning algorithms forindustrial applications with sustainable performance.

The industrial manufacturing companies have used digital technology for several years to improve their process by the way of approaching the power of connected sensors, data and artificial intelligence (AI) at all stages of an operation has yet to be realized on a grand scale. Industrial 4.0 manufacturing mainly focus on the intersection of Big Data, Artificial Intelligence (AI) and IoT devices in an industrial setting, continuing the series on these technologies and the Ecosystems support. Industry 4.0 refers to the next step in industrial technology, with robotics, computers and equipmentbecoming connected to the Internet of Things (IoT), and enhanced by machine learning algorithms. Advances in sensortechnology and connectivity modules have allowed more equipment to be measured, monitored, and tracked between sites, and orchestrated from a central, remote location. Managers, Executives and Scientists use this accessibility and improve the productivity of the whole operation. The rise of cloud computing and the consequent falling costs of data storage, a huge amount of data can now also be stored and fed into machine learning algorithms to help automate specific processes within an organization.

II. INTELLIGENT MANUFACTURING

The Industry 4.0, manufacturing systems are updated to an intelligent level. Intelligent manufacturing takes advantage of advanced information and manufacturing technologies to achieve flexible, smart, and reconfigurable manufacturing processes in order to address a dynamic and global market. The entire product life cycle can be facilitated using various smart sensors, adaptive decision-making models, advanced materials, intelligent devices, and data analytics (Li B et al., 2017). One form of realization of this concept is the Intelligent Manufacturing System (IMS), which is considered to be the next-generation manufacturing system that is obtained by adopting new models, new forms, and new methodologies to transform the traditional manufacturing system into a smart system. In the Industry 4.0 era, an IMS uses Service Oriented Architecture (SOA) via the Internet to provide collaborative, customizable, flexible, and reconfigurable services to end- users, thus enabling a highly integrated human-machine manufacturing system. AI plays an essential role in an IMS by providing typical features such as learning, reasoning, andacting. With the use of AI technology, human involvement in an IMS can be minimized (Ray et al., 2017).

Future research perspectives for intelligent manufacturing in the Industry 4.0 era are believed to be in the following areas: a generic framework for intelligent manufacturing, data-driven intelligent manufacturing models, IMSs, human- machine collaboration, and the application of intelligent manufacturing.

A generic framework for intelligent manufacturing

In order to fully implement intelligent manufacturing, platform technologies such as networks and the IoT, virtualization and service technology, and smart objects/assets technology should be focused on, since increasing amounts of customized requirements from customers will increase the costof manufacturing. Platform technology is able to reduce cost by making full use of flexible and reconfigurable manufacturing systems through intelligent design, production, logistics, and supply chain management. Multiplex platform technology, especially for design and development, will provide a novel solution to address the issue of highly customized products (Simpson et al., 2014). The service oriented concepts for intelligent manufacturing key components in Industry 4.0 in research topics are categorized into smart design, smart machines, smart monitoring, smart control, and smart scheduling. (Ray et al., 2017).

2.1.1 Smart Design. With the rapid development of new technologies such as VR (Virtual Reality) and Augmented Reality (AR), traditional design will be upgraded and will enter into a “smart era.” Design software such as Computer-Aided Design (CAD) and Computer-Aided Manufacturing (CAM) is able to interact with physical smart prototype systems in real time, enabled by three-dimensional (3D) printing integrated with CPSs and AR (Ray et al., 2017).

2.1.2 Smart Machines: In Industry 4.0, smart machines can be achieved with the help of smart robots and various other types of smart objects that are capable of real-time sensing andof interacting with each other. For example, CPS-enabled smart machine tools are able to capture real-time data and send them to a cloud-based central system so that machine tools and their twinned services can be synchronized to provide smart manufacturing solutions (Ray et al., 2017).

2.1.3 Smart Monitoring: Monitoring is an important aspect for the operations, maintenance, and optimal scheduling of Industry 4.0 manufacturing systems. The widespread deployment of various types of sensors makes it possible to achieve smart monitoring. For example, data and information on various manufacturing factors such as temperature, electricity consumption, and vibrations and speed can be obtained in real time (Ray et al., 2017).

2.1.4 Smart Control. In Industry 4.0, high-resolution, adaptive production control (i.e., Smart Control) can be achieved by developing cyber physical production control systems. Smart control is mainly executed in order to physically manage various smart machines or tools through a cloud-enabled platform. End-users are able to switch off a machine or robot via their smart phones (Ray et al., 2017).

2.1.5 Smart Scheduling: The smart scheduling layer mainly includes advanced models and algorithms to draw on the data captured by sensors. Data-driven techniques and advanced decision architecture can be used for smart scheduling. For example, in order to achieve real-time, reliable scheduling andexecution, distributed smart models using a hierarchical interactive architecture can be used (Ray et al., 2017).

2.2. Data Driven Intelligent Manufacturing (IM) Models

With the large increase of digital devices carrying RFID and/or smart sensors in manufacturing, enormous amounts of data will be generated. Such data carry rich information or knowledge that can be used for different decision-making situations (Zhong RY et al., 2016). Therefore, the effective usage of data not only involves improving manufacturing efficiency, but also drives greater agility and deeper integration with other parties such as logistics and supply- chain management entities.

Dynamics in a production system will significantly influence quality and efficiency. Data-driven models are able to make full use of historic or real-time data for system diagnosis or prognosis, based on information or knowledge integration, data mining, and data analytics (Zou J et al., 2017). It is clear that in the future, data-based or knowledge- driven models and services will be largely adopted for intelligent manufacturing. One key research area is the integration of cloud services with knowledge management in a platform that is able to provide enterprise services such as intelligent design and manufacturing, production modeling and simulation, and logistics and supply-chain management. This platform will accumulate a vast amount of production data from various manufacturing objects equipped with smart sensors or digital devices, in order to combine human, machine, material, job, and manufacturing logics. An intelligent workshop operation center over the cloud may use self-learning models to build more advanced or intelligent models and algorithms for advanced decision-making in manufacturing systems (Ray et al., 2017).

2.3 Intelligent Manufacturing Systems (IMS)

The design and development of IMSs require more and more collaboration across the whole range of enterprises and industry. Collaborative manufacturing models or mechanisms such as a cloudbased manufacturing resources/objects management system will centrally control the large variety of production objects so that IMSs are able to work properly and effectively (Zhong RY et al., 2015). A key research area in the future involves decentralized control service, from whence each intelligent component in the system can make self- adaptive decisions. For example, intelligent components operating in each stage of an assembly line can seamlessly cooperate with moving pieces and other lines to maintain the synchronized production rhythm. Autonomous intelligent manufacturing units are very important for IMSs. They are based on more advanced embedded chips or sensors that can automatically recognize components, monitor online facilities, and move workpieces. Manufacturing executions based on this system will be more efficient with the help of advanced autonomous unmanned devices such as automated guided vehicles (AGVs). Key research in the future may focus on the enabling technologies for IMSs, such as AR and VR, for a safer production plant (Yew AWW et al., 2016) Advanced manufacturing processes and services will be easily integrated into IMSs, so an open platform will be beneficial for manufacturing companies, and particularly for SMEs.

Application of Intelligent Manufacturing (IM)

Intelligent manufacturing applications for entire industries are significant in Industry 4.0, in which real-life companies can benefit from cutting-edge technologies. An agent-based framework for IMSs will be a suitable solution to the problem of production planning and scheduling, workshop monitoring and control, and warehouse management. Agent-based implementation is able to define workflows and follow manufacturing logics so that the decision-making related to these elements can be effectively facilitated. Taking automation in manufacturing systems as an example, multi-agent technologies can be used to parallel-control robots that are enabled by an agent-based architecture with distributed agents. in order to ease the implementation of IM (Priego R etal. 2017). Another future implementation of IM is cloud-basedsolutions; these use cloud computing and SOA to share or circulate manufacturing resources. Several different cloud platforms will be established to make full use of IMSs so that manufacturing capabilities and resources can provide on-demand services to end-users (Ray et al., 2017).

2.4 Human Machine Collaboration

Under Industry 4.0, humans and machines will work collaboratively by using cognitive technologies in industrial environments. Intelligent machines will be able to help humans to fulfil most of their work using speech recognition, computer vision, machine learning, and advanced synchronization models (Antrobus V et al., 2017). Thus, advanced learning models for machines such as robots are important so that humans and machines develop skills that complement each other under any working conditions. One future research direction is an approach for “human-in-the- loop” machine learning, which enables humans to interact efficiently and effectively with decision-making models. Thus, data-enabled machine learning mechanisms may provide pathways by using human domain expertise or knowledge to better understand the collaboration. For example, traditional machine learning systems or algorithms can be interjected with human knowledge so that a real-world sensing system can help improve human-machine interactions and communications (Ray et al., 2017).

Machine intelligence plays an important role in supporting human-machine collaboration, since machines will be providing assistance with every job, every role, and anything that is done in manufacturing sites where dynamic situations are present (Xu X, 2017). Safety issues may be a crucial research topic, as machines equipped with intelligent control systems begin to behave and act as humans in real-life manufacturing sites such as workshops. Such machines can easily communicate with workers through self-learning and evolutionary procedures. For example, intelligent human- machine integration for automating design can be realized from ontology-based knowledge management with local-to- global ontology transitions and the epistemology- based upward-spiral cognitive process (Yin YH et al., 2015) in order to ultimately achieve manufacturing intelligence in the future.

III. MAIN CHALLENGES OF INDUSTRIAL 4.0 WITHARTIFICIAL INTELLIGENCE (AI)

The shift in manufacturing processes will be settled in the employment of smart objects interacting with each other and with the user. It has already been stated that the basic pillar in this trend will be defined by the combination of hardware and software into embedded systems denominated Cyber Physical Systems (CPS) that will make use of the internet of things (IoT) and Big Data to connect every device, that will have its correspondent identifier and basic computer capabilities in order to sense and/or act. Hence, several tools are needed not only to conform and function in the embedded system, but to develop as well some kind of interface or network in order to extend it, which constitutes the base for the development of this industry 4.0, from the sensors, actuators and control units that gathered information provided by different elements inthe process, to a cyber physical system that can manage this information and make decentralized decisions, to the smart machines that will follow the self-deduced actions to take, to the platform that must sustain great flows of information, to even the simulation of processes and design and testing of prototypes based on intelligent and self-aware systems.

Indeed, the science of artificial intelligence is settled in the same principles (Statistical Methods, Machine Learning, Mathematical Optimization, Neural Networks, Probability, Computational Intelligence etc) that the ones that will help constructing the combination of physical and conscience worlds. These include autonomous robots that can work collaboratively with humans in safe conditions, simulation and virtualization tools to help during decision-making stages or additive manufacturing. (Dopico M et al., 2016).

3.1 The Internet of Things (IoT) And Cyber PhysicalSystems (CPS)

Citing the Federal Ministry of Education and Research in Germany (BMBF): “Industry is on the threshold of the fourth industrial revolution. Driven by the internet, the real and virtual worlds are growing closer together to form the Internet of Things”. Hence, IoT can be defined as the network system that supports the tools for communication between smart devices and their interconnectivity. In the configuration ofIoT, two separate and equally important variables are required:On the one hand, a complete gear of sensors and tags in chargeof capturing the information that the different stages and machines in the process generate; and on the other hand, communication software protocols to transfer this information to a central server.

The CPS is then the final responsible for the management and analysis of the information sent by these interconnected systems between its physical assets and computational capabilities; while the advanced connectivity network integrated in the IoT must ensure real time data acquisition from the physical world, as well as posterior information feedback from the cyber space (Abu-Elkheir M et al., 2013) These capacities allow self-comparison between present and past states, and assist in the decentralized decisions of recommended course of action, making machines self- configure and self-maintainable. The structure of a CPS can bedivided in different levels to make machines self-aware and self-adaptive (as shown in Fig. 2.) are Smart Connection Level (gathering of all information); Data-to-information Conversion Level (extract the relevant information); Cyber Level (includes the virtualization hub to exchange information through other cyber interfaces); Cognition Level (where optimization decisions take place); and Configuration Level (for feedbackdeployment) (Lee J et al., 2015).

Last fundamental concepts for this pillar of industry 4.0 are Big Data and cloud computing, which creates a medium that can handle all the managed information by CPS and IoT. Huge amounts of information is expected to be stored and processed, so later on can be accessible from anywhere at any time, thus, cloud computing constitutes an optimum solution for storage performance, as well as Big Data analysis aids in the management of the information.

The capacity to support and control big flows of information is one of the most important applications of industry 4.0, which relies on the maintenance of artificial intelligence networks supported by digital product memories, translated into the collection of all data records for all data stages during the product life cycle, for posterior analysis, that could lead to newer and innovative methodical approaches forplanning and development of products (Lee J et al., 2015) & (Lasi H et al., 2015)

3.2 Autonomous Robots

Once the information has been received and analyzed; and decisions have been taken, another logical step consists in the actual execution of those measures. In the context of industry 4.0, self-learning and self-configurative robots are in charge of these actions, in complete collaboration with human workforce. Traditional concepts like proper design, operation erformance, energy efficiency or maintenance are still important, with the difference that autonomous robots willhave the capacity of managing some of this data to adjust and suggest changes by themselves to improve and predict their functionality and flexibility (Lee J et al., 2014).

The proper combination of sensors, artificial intelligence and even robotic design are fundamental in this field. Technological enhancements have already improved robotics substantially over the past years, making robots suitable for almost every sector. The increasing autonomy of robots will lead, however, to another consequence, which is the need for the establishment of safety protocols for operators working in the same area (Lee J et al., 2014).

Machines from this new revolution and AI networks must ensure the means to support an infrastructure where robots are intended to work collaboratively with humans, facilitating their work instead of replacing them. Machine vision sensors, AI and learning software are the three most important variables that will allow the synergy between independent productive entities and shop-floor operators in a safe environment (Lee J et al., 2014).

3.3 Additive Manufacturing

Additive Manufacturing or 3D printing, that is the capability to produce three-dimensional objects directly from virtual models, is another pillar of industry 4.0, with multiple possibilities, especially for designing and testing prototypes, where newer methods of modeling and reference models are continuously appearing without the need of moulds, so one machine can be used for the manufacture of different products, thus reducing production costs (Lasi H et al., 2014). Even though so far, this application has not been broadly applied mainly because of slow production rates, few available materials and high prices, great developments are being made to solve these issues and improving the efficiency of producing individually customized products, allowing for rapid prototyping and highly decentralized production processes. The expectations from Industrial AI are versatile and enormous and even a partial fulfilment of these expectations would represent unique and real challenges of applying AI to industries. (Jay Lee et al., 2018)

3.4 Machine To Machine Interactions

While AI algorithms can accurately map a set of inputs to a set of outputs, they are also susceptible to small variations in the inputs caused by variations from machine to machine. It needs to ensure that individual AI solutions do not interfere with the working of other systems, further down the line.

3.5 Data Quality

AI algorithms require massive and clean data sets with minimum biases. By learning from inaccurate or inadequate data sets, the downstream results can be flawed.

3.6 Cybersecurity

The increasing use of connected technologies makes the smart manufacturing system vulnerable to cyber risks. Currently, the scale of this vulnerability is under-appreciated and the industry is not prepared for the security threats that exist. (Tuptuk N et al., 2018).

3.7 Augmented Reality, Simulation And Visualization Systems

Every decision, whereas it is related with logistics, manufacturing or future changes must be sustained in wellfounded arguments. Industry 4.0 technologies will ease the deployment of simulation scenarios where different configurations can be tried and tested before their actual implementation, thus allowing the implantation of more complex systems. Simulation of how changes can affect process behavior are a huge benefit towards the prediction of how these resources or services will impact final value added for end users (Monostori L, 2014). Again, artificial intelligence can provide the means for simulation in every stage of the life cycle of a product (from model and design, to functionality prediction). One example of this application mayconsist in the evelopment of newer methods of modeling and reference models, like Integrated Computational Materials Engineering (ICME), where the performance of design materials and dimensions can be tested before construction of the element (Lasi H et al., 2014). However, this pillar of industry 4.0 does not only refer to product properties, being possible as well the implementation of virtualization technology that creates complete digital factories which can simulate the entire production process, in order to optimize layout disposition. This is especially useful for launching new products in already existing plants; by first simulating and verifying virtually the consequent impact in production and human-machine interactions; and only when the final solution is ready, the physical map is done, meaning that all software, parameters, and numerical matrixes are uploaded into the physical machines controlling the production. (Dopico M et al., 2016)

IV. ICT METHODOLOGIES IN EMBEDDED SYSTEMS

The previous section has shown the most important tools for the development of industry 4.0. As it was said before, the combination of hardware and software into smart embedded systems will be greatly resting in AI applications. However, sometimes those smart devices are generally referred to as a whole scale with blurred barriers, where it is difficult to establish when one element ends and the other starts. Forexample, during the first years of development of this concept, IoT was proposed to refer just to uniquely identifiable interoperable connected objects with radiofrequency identification (RFID) technology. Later on, however, as the connectivity of these networks were getting bigger and including new technologies and concepts, the term was growing with it to include all these innovations, applied to measure, identify, position, track and monitor objects (Bi Z et al., 2014) referring now to IoT more as a dynamic global network where self-conscious objects connect with each other. In this new context where CPS can be considered the proper “brains” inside industry 4.0, one way to establish some frontiers can be to consider IoT as the global framework where identification and sensor technologies become integrated with interpretation technologies like CPS. In other words, CPS forms part of IoT´s new step towards its development (Campbell I et al., 2012) & (Da Xu et al., 2014), with the help of ICT elements to guide the autonomous communication between all of them. The following section will depict the most relevant parameters in this established network by IoT and CPS that constitute the embedded system; including sensoric equipment, their communication protocols through software architecture, standardization languages for the gathered information, big data management, cloud computing and middleware connectivity, or architecture guidelines for construction of CPS (Dopico M et al., 2016).

4.1 Sensors For IoT

It has been said that the integration of sensors/actuators, radio frequency identification (RFID) tags, and communication technologies served as the foundation of IoT, and consequently industry 4.0. According with that line of hinking; from a conceptual standpoint, sensors settle the principles for which smart objects are able to (Monostori L, 2014) Be identifiable, communicate and interact with each other, with users and/or other entities within the network. In the context of identification, sensing and communication devices, radio frequency identification systems (RFID) are the key components for industry 4.0 . (Dopico M et al., 2016). RFID systems are composed of one or more readers and several RFID tags. Tags are characterized by a unique identifier and can be applied to objects or people. The readers are used to trig the tag transmission by generating an appropriate signal, which represents a query for the possible presence of tags in the surrounding area and for the reception of their IDs. From a physical point of view, a RFID tag is a small microchip attached to an antenna (that is used for both receiving the reader signal and transmitting the tag ID) in a package which usually is similar to an adhesive sticker. Dimensions can be very low (0.4x0.4x0.15 mm) (Dopico M et al., 2016) depending on how the energy is supplied, we have to differ between passive RFID tags (energy for operation is supplied by the RFID interrogation signal itself), active tags (on-board power source feeds the on-board receiver and transmitter, allowing for an increased radio range), and semi- active or semi-passive, where on-board power source is used to feed the microchip, whereas transmission is either active (semi-active) or performed using back-scattering (semi- passive) (Monostori L, 2014).

4.2 Communication Protocols For Sensors

Along with RFID technology, other complementary devices for identification are sensor networks or wireless sensor networks (WSN) (Abu-Elkheir M et al., 2013). Sensor networks consist of a certain number (which can be very high) of sensing nodes communicating in a wireless multi-hop fashion (Da Xu et al., 2014) & (Gubbi J et al., 2013). Usually nodes report the results of their sensing to a small number (in most cases, only one) of special nodes called sinks. Typically, a node, which is the WSN core hardware, contains sensor interfaces, processing units, transceiver units and power supply (Gubbi J et al., 2013). In fact, they can cooperate with RFID systems to better track the status of things, thus augmenting the awareness of a certain environment and act as bridge between physical and digital world, helping the exchange of information inside the network. Some of the most common hardware and software available for WSN that serve as communication protocols with unique addressing schemes and standards are IPv6 (to connect unlimited number of devices) (Bi Z et al., 2014) & (Gubbi J et al., 2013). WiFi and Wimax (to provide high-speed and low cost communication) or Zigbee and bluetooth (for local communication; or others like WLAN, M2M or RFID. (Dopico M et al., 2016) & (DaXu et al., 2014)

4.3 Big Data, Cloud Computing

The great flow of information in these embedded systems needs for technologies that ease the automation, and Big Data can be a solution for that, by enhancing as well important variables like mobility, flexibility and energetic efficiency, providing a temporally and spatially independent access to them (Monostori L, 2014). The application of Data Mining serves to sustain the analysis, modeling, simulation, fusion and computation, and scientific prognosis for decision making (Bi Z et al., 2014). Cloud Computing is, on the other hand, basically a large-scale, low cost flexible processing unit, based on IP connection for calculation and storage. The need for cloud computing is founded in the fact that some relation must be established between identification devices towards a storage for huge amounts of information (Abu-Elkheir M etal., 2013) and the need for a centralized infrastructure to support this storage and posterior analysis (Gubbi J et al., 2013).

They are in need of a radical change known as Industry
4.0. Integration of AI with recent emerging technologies such as Industrial Internet of Things (IIoT), big data analytics, cloud computing and cyber physical systems will enable operation of industries in a flexible, efficient, and green way. Since Industrial AI is in infancy stage, it is essential to clearly define its structure, methodologies and challenges as a framework for its implementation in industry. The deign part of an Industrial AI ecosystem, which covers the essential elements in this space and provides a guideline for better understanding and implementing it. Furthermore, the enabling technologies that an Industrial AI system can be built upon aredescribed. (Jay Lee et al., 2018)

V. INDUSTRY 4.0 WITH AI KEY ELEMENTS: ABCDE

The key elements in Industrial AI can be characterized by “ABCDE”. These key elements include Analytics Technology (A), Big Data Technology (B), Cloud or Cyber Technology (C), Domain Know How (D) and Evidence (E). Analytics is the core of AI, which can only bring value if other elements are present. Big data technology and Cloud are both essential elements, which provide the source of the information (data) and a platform for Industrial AI. While these elements are essential, domain knowledge and Evidence are also important factors that are mostly overlooked in this context. Domain knowhow is the key element from the following aspects:

1) understanding the problem and focus the power of Industrial AI into solving it;

2) understanding the system so that right data with the right quality can be collected;

3) understanding the physical meanings of the parameters and how they are associated with the physical characteristics of a system or process; and

4) understanding how these parameters vary from machine to machine. Evidence is also an essential element in validating Industrial AI models and incorporate them with cumulative learning ability. By gathering data patterns and the evidence (or label) associated with those patterns can only we improve the AI model to become more accurate, comprehensive and robust as it ages. (Jay Lee et al., 2018)

5.1 Industrial AI Eco-System

Industrial AI Ecosystem as shown Fig. 1. which defines a sequential thinking strategy for needs, challenges, technologies and methodologies for developing transformative AI systems for industry. Practitioners can follow this diagram as a systematic guideline for developing a strategy for

Industrial AI development and deployment. Within the targeted industry, this ecosystem defines the common unmet needs such as Self-aware, Self-compare, Self-predict, Self- optimize and Resilience. This chart also includes four main enabling technologies including Data Technology (DT), Analytic Technology (AT), Platform Technology (PT) and Operations Technology (OT). These four technologies can better be understood when put in the context of the Cyber- Physical Systems (CPS), proposed in (Lee J et al., 2015). As depicted in Fig. 2. these four technologies (DT, AT, PT and OT) are the enablers for achieving success in Connection, Conversion, Cyber, Cognition and Configuration, or 5C. This section of the paper provides a brief description of each of the mentioned technologies. (Jay Lee et al., 2018)

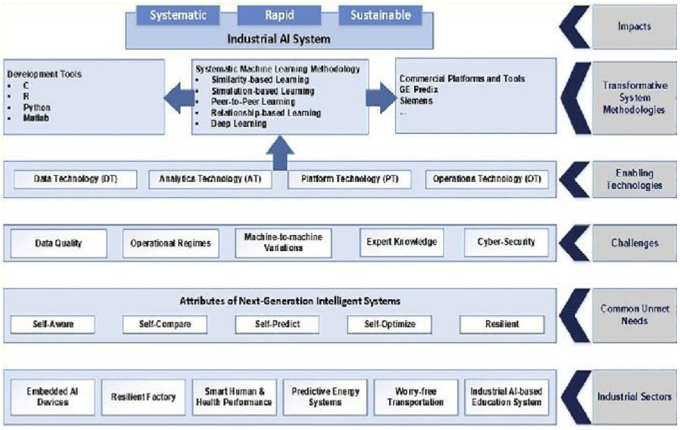

Fig. 1. Industrial AI Eco-system. Source: Researchgate.net

5.1.1 Data Technologies (DT)

Data Technologies are those technologies, which enable successful acquisition of useful data with significant performance metrics across dimensions. Therefore, it becomesa co-enabler of the 'Smart Connection' step in the 5C architecture shown in Fig. 2. by identifying the appropriate equipment and mechanism for acquiring useful data. The other aspect of data technologies is data communication. (Jay Lee et al., 2018).

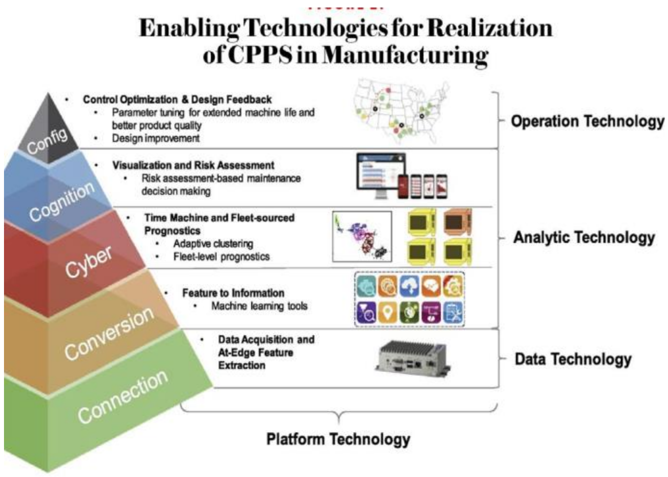

Fig. 2. Enabling technologies for realization of CPS in manufacturing. Source: Manufacturingleadeshipcouncil.com

Analytics Technologies (AT)

Analytics Technology converts the sensory data from critical components into useful information. Data driven modeling uncovers hidden patterns, unknown correlations and other useful information from manufacturing systems. This information can be used for asset health prediction which can be used for machine prognostics and health management. Analytic Technologies integrate this information with other technologies for improved productivity and innovation. (Jay Lee et al., 2018).

5.1.2 Platform Technologies (PT)

Platform technologies include the hardware architecture for manufacturing data storage, analysis and feedback. A compatible platform architecture for analyzing data is a major deciding factor for realizing smart manufacturing characteristics such as agility, complex-event processing, and so on. Three major types of platform configurations are generally found – stand-alone, embedded and cloud. Cloud computing is a significant advancement in Information and Communication Technologies with regard to computational, storage and servitization capabilities. The cloud platform can provide rapid service deployment, high level of customization, knowledge integration, and effective visualization with high scalability. (Jay Lee et al., 2018).

5.1.3 Operations Technology (OT)

Operation technology here refers to a series of decisions made and actions taken based on the information extracted from data. This machine-to-machine collaboration can be between two machines in a shop floor, or machines in two different factories far apart. They can share their experience on how adjusting specific arameters can optimize performance, and adjust their production based on the availability of other machines. In an industry 4.0 factory, Operations technology is the last step leading to the following four capabilities: 1) Self- aware 2) Selfpredict, 3) Self-Configure and 4) Self-Compare. (Jay Lee et al., 2018).

CONCLUSION

AI is not about sentient robots and magic boxes. AI is a science and a set of computational technologies. AI encompasses machine learning (machines that can learn from data – algorithms adjusting themselves) and deep learning (a combination of algorithms that are mutually linked). The overview of Industrial AI and Industrial AI Eco-system in today's manufacturing, this paper explored and provide a guideline for strategizing the efforts toward realization of Industrial AI systems and Industrial AI Eco-system. Within AI data scientists extract knowledge and interpret data by using the right tools and statistical methods. The machines learn to recognize patterns in the data that it is fed to them and map these patterns for future outcomes implementations. There are three main steps to implement AI in future industry manufacturing such as Develop an AI strategy and roadmap and establish AI capabilities with skills in future Industry Manufacturing Systems (IMS).

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