

Approaches to a Practical Implementation of Industry 4.0

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Abstract—The arrival of Industry 4.0 has popularised the concept of smart interactions between humans and the physical world that could realise the synergistic integration of intelligent manufacturing assets. However, a systematic and cogent approach to the practical and profitable application of Industry 4.0 is still missing. This paper presents practical approaches to the application of Industry 4.0 to manufacture with the aim of strengthening its competitiveness and meeting the growing serious challenges that threaten its profitability and survival. Precision Additive Metal Manufacturing is utilised in this study for demonstration purposes. A conceptual framework combined with two practical modules available in the market, a “native-design” and “Plug and Play”, is proposed. These approaches offer flexible prototypes with sequential procedures that ultimately would allow for easy employment of Industry 4.0, and will help remove technical barriers to the development of manufacturing industry in the domain of Industry 4.0.

Keywords—Industry 4.0; IoT; Cloud-based big data analytics; CPS; precision additive metal manufacturing

I. INTRODUCTION

Although European industrial sectors continue to receive significant investment, unfortunately, the generated profit does not follow the same positive trend, which negatively influences their growth. Figure 1 illustrates the relative proportions of world global manufacturing outputs for gross domestic products (GDP) between 2003 and 2011 [1]. It is clearly seen that while the share of global manufacturing output for USA and European manufacturing communities have lessened consistently, the Chinese share has had a strong upward trend.

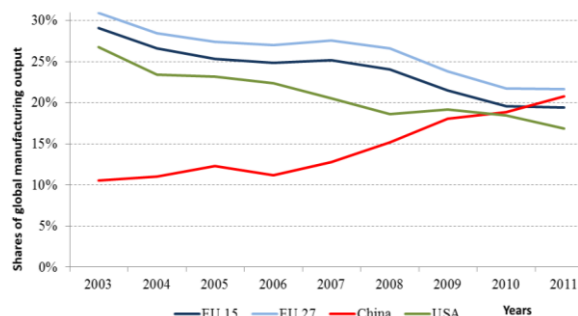


Figure 1: Shares of global manufacturing output until 2011 [1]

This observation certainly reflects the fierce competition between the well-established manufacturing communities in USA and Europe, and the new superpower player, China, who can offer highly competitive industrial products of good quality at low cost, due to lower expenses (both labour and operating costs) [2]. This has driven some European manufacturers to invest outside Europe in other growing economies. This objectively works against the advancement of European industry and poses serious threats to European economies. In view of this situation, the transition to the fourth industrial generation “Industry 4.0” has become indispensable as a robust solution for the survival of European industry [3]. In particular, the existing capabilities of conventional manufacturing technologies are no longer adequate to face the current industrial challenges. This has motivated manufacturers and researchers to develop different approaches to implement Industry 4.0 for a range of industrial applications, which would ultimately strengthen the competitiveness of the European economy [4].

Literally, the term “Industry 4.0” stands for smart manufacturing, involving Data Acquisition, Cyber-Physical Systems (CPSs), Internet of Things (IoT), Cloud/Edge Computing, Big Data Analytics (BDA), and Enterprise Resource Planning (ERP) [3]-[5].

Since information is the key factor in implementing Industry 4.0, data acquisition techniques play an important role in any proposed approach [5]. Different convenient algorithms have been utilised for sensing, acquiring, and processing of signals. However, CPSs are central in Industry 4.0, to monitor and control physical processes. The industry basically builds a seamless link between the mechanical and digital systems combined with a data exchange system onto the CPS [6]. The digital system can be designed based on convenient hybrid approaches using hardware components such as embedded systems and computers with integrated software solutions.

In Industry 4.0, communication technology is empowered by the IoT, which enables system components, processed products and people to concurrently exchange information [7][8]. This technology allows for acquiring massive data, where its analysis can be performed via cloud computing and BDA. This facilitates modelling, simulation, and virtualisation of the manufacturing process [7]. However, cloud computing and BDA are also used to feed the

Manufacturing Execution Systems (MES), in order to monitor the work in progress and enables the simultaneous connection of partners, suppliers, customers and other stakeholders [9][10].

Some of these components have already been utilised on an industrial scale. However, the synergistic integration of the aforementioned fragments is the most challenging issue that still needs addressing, and could eventually offer a smart solution to manufacturing problems [10]. A capable and insightful approach on how to apply Industry 4.0, practically and profitably, is still not available. The aim of this paper is to provide a generic practical model on how to implement Industry 4.0. Therefore, metal additive manufacturing, as a good example of the digital manufacturing method, is utilised in this study to improve obtainable precision and accuracy of the manufacturing processes. This research was inspired by project Precision Additive Metal Manufacturing (PAM²).

The following sections of this paper are organised as follows. First, some of the expected benefits and challenges that are associated with the implementation of Industry 4.0 are discussed. After that, a theoretical Industry 4.0 model followed by two practical approaches are detailed. Finally, conclusions are drawn and future perspectives presented.

II. INDUSTRY 4.0: BENEFITS AND CHALLENGES

The 4th industrial revolution, currently in-progress, has been promoted by the advent of recent advanced information- and communication-driven technologies, aiming at realising the potential of cross-linking intelligent manufacturing operations with automated near real time data acquisition and simulation technologies, see Figure 2. This offers the possibility of instantaneous identification of physical problems with the almost concurrent production of necessary corrective actions which are expected to optimise the performance of the entire manufacturing system [11][12]. The expected outcomes of the implementation of Industry 4.0 in manufacturing processes and the challenges associated with this implementation are presented in the following sub-sections.

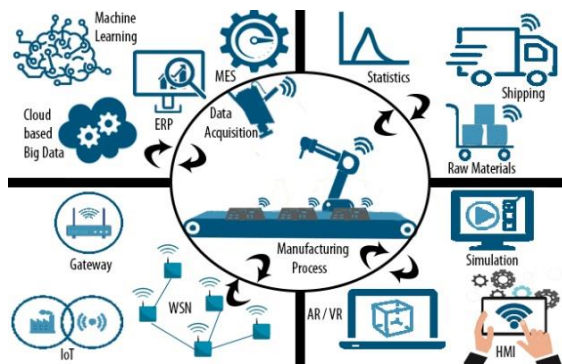


Figure 2: Industry 4.0 Framework

A. Benefits

The added value to the manufacturing processes can be seen in the following four phases.

1. Virtual design and pre-manufacturing validation

For additive manufacturing technology, Industry 4.0 offers an upgraded version of the design tool, which especially integrates virtual reality (VR) and augmented reality (AR) into the design environment. In particular, computer-aided design (CAD) will be able to interface with VR and AR to present in virtual form the physical product, and thus enable assessment of the design prior to actual manufacturing [13].

2. Corrective actions of manufacturing process

Any fabrication process depends on a controller to secure a stable response under different process conditions. Industry 4.0 presents smart pilot actions based on the CPS and cloud computing. In particular, CPS works to transfer physical parameters (thermal, power, and geometry) to the cloud to be processed, where optimal control decisions will be sent back to the physical system. If the information indicates an issue such as too high power consumption, then the system has to take an appropriate action.

3. Self-decision and big data analytics

Smart decision making is an advantage of Industry 4.0. The ultimate goal of deploying widespread sensors is to achieve smart decision making through comprehensive data collection. The realisation of smart decision making requires real time information sharing and collaboration. Big data and its analytics play an important role in smart decision making tasks, including data-driven modelling, data-enabled predictive maintenance, ERP and marketing.

B. Challenges

Although applying Industry 4.0 will generate new opportunities and provide enormous benefits, it will not be a bed of roses. There are some challenges that need addressing prior to swinging into action.

Industrial challenges generally can be understood to act as a barrier to the advancement of manufacturing technology and the challenges generally increase in complexity over time. On the other hand, to move forward, industrial capability has to grow beyond existing levels, and this is what Industry 4.0 is intended to help accomplish.

The following areas are examples of potential challenges to realising Industry 4.0:

1. Ensure integrity

Integration compatibility is one of the main issues to be considered when applying Industry 4.0. As previously stated, Industry 4.0 has different elements, which need to be suitably integrated to attain the best possible performance of the developed system. In particular, it is a communication challenge to tune the sub-systems' components (nodes) to work in synchronised time domains based on the desired priorities.

2. Ensure security

Since massive data sets with important and confidential information will be exchanged, strenuous effort must be taken to ensure secure data processing among and between Industry 4.0 systems; Data Acquisition, CPSs systems, IoT, Cloud computing, BDA, and ERP. The encryption used must resist cipher analysis (attack), which poses formidable challenges on the level of security and data protection.

3. Power consumption

Reducing power consumption is of significant importance to stakeholders, and is considered one of the major priority parameters in a good design. Generating an optimal design to reduce power consumption without affecting the work performance is still a major design issue.

C. Industry 4.0: Human-Machinery Interaction

The industry 4.0 will introduce entirely different ways of smart interaction between human and the physical world. Especially, Industry 4.0 provides a user-friendly interface for humans to remotely interact with machines. Advancement of Industry 4.0 allows users to have remote interaction with manufacturing processes, and to enhance the manufacturing parameters using this interface. HMI will be developed for mobile, web, and other techniques [6]. Based on the developed techniques on HMI, the HMI will dramatically change the way people work together and also the interaction among industrial partners. Thus, attention should be paid to the working environment to persuade people to accept the new procedures and changes. The results of using HMI is playing an important role in using the productivity and manufacturing process optimisation such as enhancing of monitoring, reporting, quality control, and other manufacturing process.

Human machine interaction in industry can also take place on-site. On site interface/control can be implemented via local area network (LAN). Both aforementioned interactions, remote and on site interfaces, could be realised via contact and non-contact methods. Examples of Contact HMI are Graphical User Interface (GUI), Menu Driven Interface, Command Line Interface (CLI) and Touch Sensitive Interface. However, Hand Gesture Recognition and Voice Driven Interface (Voice recognition) are methods of non-contact HMI, as shown in Fig. 3. To utilise one or more of the formerly mentioned techniques, an algorithm has to be designed that considers constraints related to machine, operation, work-piece and safety environment.

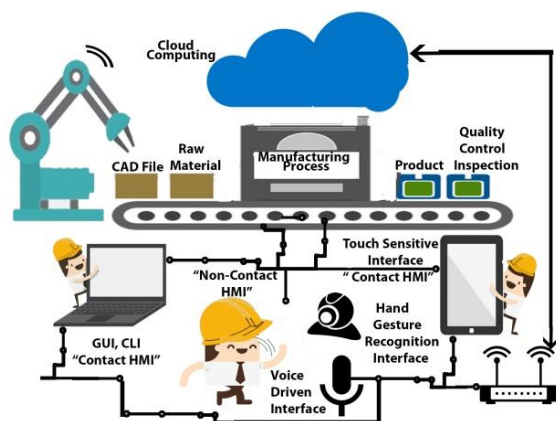


Figure 3: Proposed Human-Machinery Interaction

III. THEORETICAL APPROACH

German chancellor Angela Merkel in a visit to the Siemens “smart” factory in February 2015, defined Industry 4.0 as “the fusion of the online world and the world of industrial

production” [12]. Technically, Industry 4.0 can be simply defined as the digitising of the manufacturing processes combined with real time data acquisition to server computing, cloud and/or edge, where the acquired data is processed and analysed to simulate the real world [5][6].

One of the main objectives of developing manufacturing solutions based on Industry 4.0 concepts is to monitor industrial processes in order to optimise them.

Virtual simulation can be conducted based on real time data acquisition to enable monitoring of the real state of the manufacturing process. This real time monitoring helps to reduce the time taken for maintenance, with the added possibility of almost instantaneously taking necessary corrective measures, by either human to machine, or learned algorithms to the machine, as shown in Figure 4.

Figure 4 illustrates proposed approaches to implementing Industry 4.0 in additive manufacturing processes. The approach starts with the Data Acquisition module, where an invasive or non-invasive sensor takes a measure of the relevant industrial parameter to be then digitised. Data Acquisition is the process of sensing, sampling, acquiring and measuring an electrical or other physical signal representing the real world and converting it into numeric values so that it can be analysed using statistical techniques.

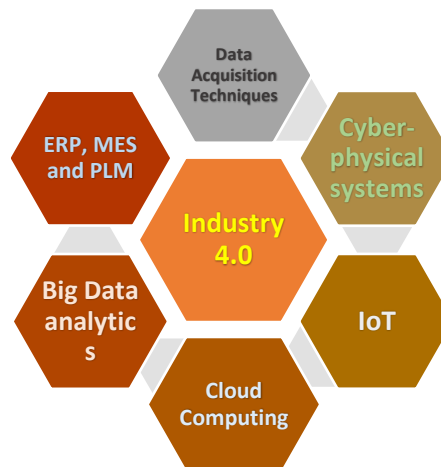


Figure 4: Industry 4.0: theoretical approach

The data acquisition is considered as the input of the CPS which processes information received and analyses it to perform the digitalised manufacturing process as a real-time simulation. This simulation is the core of the monitoring process using the CPS approach.

IoT plays an important role on the approach, as shown in Figure 4. The IoT technology helps the nodes (products, machines parts, controllers, users, and manufacture districts) to exchange the information in a way that increases the efficiency of the manufacturing process. The collected information helps human/machine learning algorithms to solve serious decision/estimation problems. The proposed study interlinks with the IoT based on a cipher algorithm sufficiently robust to protect against security threats. Also, the proposed IoT platform and software algorithms are designed for low power consumption.

Edge computing “refers to the enabling technologies allowing computational processing to be performed at the edge of the network, on downstream data on behalf of cloud services and upstream data on behalf of IoT services” [15]. Based on the above definition, edge computing can be described as a computing technique for processing acquired data from machines (IoT devices) and generating a pre-analysis/ simulation at the edge of the network (on site) before sending it to the cloud computing to avoid latency problems, while cloud computing consumes time but gives stable and independent analysis and simulations. In the proposed Cyber-Physical world, edge/cloud computing will play a significant role in managing the IoT data received for processing and to feed the simulation process.

Machine Learning is a computational algorithm based on statistics and mathematical optimisation that allows for prediction, classification, recognition or decision-making [16]. Decision making using clustering of data is important in modern industrial applications. Besides, pattern recognition for validation and verification of the processing conditions (raw materials, product status during the industrial process) has received great attention by manufacturers. However, so-called deep learning such as Convolution Neural Networks (CNN) has been implemented recently in order to recognise images/frames during the industrial process [17]. Herein, machine/deep learning will be utilised to analyse the collected data and identify the proper actions to be taken for the ERP based on the predicted and estimated needs of the manufacturing scenario. The simulation process will be used to optimise the manufacturing processes by getting fully remote monitoring/interfacing of, e.g., laser direct metal deposition (LMD) or other additive processes by detecting possible defects and enhancing product quality.

IV. PRACTICAL APPROACH

A. Native design approach

The proposed design of the Industry 4.0 has been developed based on the theoretical criteria presented in the previous section. In this approach, humans can interact with multiple nodes (data acquisition, industry 4 sub-systems, products, and raw materials). These nodes can exchange data between themselves through a communication physical layer based on LoRa technology [18]. Also, each node can send or receive the data to/from a LoRa gateway wirelessly and the data can be stored on the cloud for analysis. There will be communication between user and cloud data via a Long-Term Evolution (LTE) gateway. Also, there can be communication between a human and the LTE gateway through, for example, a mobile phone. The proposed overall processes are as a shown in Figure 5.

In this design, the proposed data acquisition technique and CPS are used for extracting relevant features of the product during its fabrication by additive manufacturing. The process will be simulated based on the output of the data acquisition which, here, is a non-invasive data acquisition technique. The algorithms are based on computer vision, where the camera works to capture frames of the results of the additive

manufacturing during production, and processes them into information form. This information will, for example, contain the physical geometrical shape, temperatures and colours during the process [6].

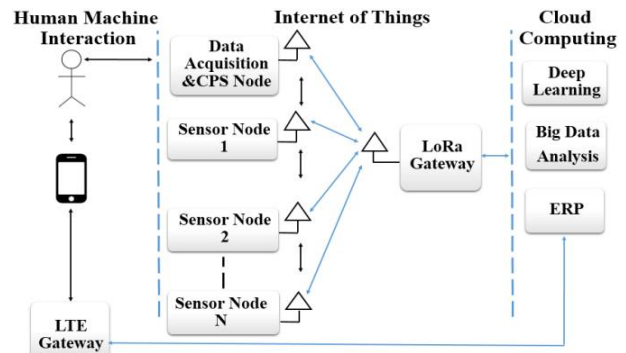


Figure 5: Proposed native design of Industry 4.0 application

The proposed sensing elements for the above approach are 2D/3D cameras, and a thermal camera. The data acquisition algorithms will work on embedded applications in visual computing. A Jetson TX1 Developer Kit enables embedded vision systems based on a GPU NVidia core structure, as shown in Figure 6. The benefits of the proposed design based on the Jetson TX1 are the low power consumption based on the Linux low power management solution of a NVidia GPU [19]. Also, it’s supported to interact with the camera module interface, as shown in Figure 6. The processing speed of the GPU NVidia is significantly higher than other models, which is crucial for investigating the process properly [20]. The device comes with a large assortment of porting interfaces, to interact with other peripherals, as shown in Figure 6. The proposed design of the CPS/inspection will be interfacing between 2D/3D cameras and thermal camera with the Jetson for extracting the relevant feature within the production process. LoRa is the proposed hardware for the communication physical layer for IoT nodes. The wireless sensor network (WSN) structure is illustrated in Figure 5.

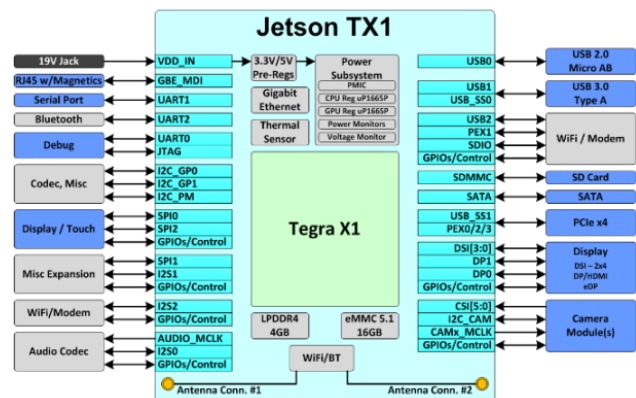


Figure 6: Block diagram of Jetson TX1 with its interfaces [13]

The proposed software will extract features of the image/frame (of the additive manufacturing product) based

on a convenient image processing algorithm. Furthermore, the feature will be compared with the feature as stored in the CAD file and an inspection result generated for quality control. The software will be supported with a wide range of libraries such as Computer vision, Deep learning and Linux platforms, based on the Jetson SDK [20].

Thus, the manufacturing process and products' states information will be extracted using computer vision system then it will be presented in form of Virtual Reality (simulation) approach. All these developments will be performed based on the Jetson kit.

The working scenario will be as follows:

1. CAD file received (Client Request).
2. Software sends the CAD file to a machine.
3. Product is being built by AM based on CPS and Inspection system;
 - 3.1 Captures frames for the process and acquires the manufacturing data such as (temperature, physical and so on).
 - 3.2 Compares the processing part with the design.
 - 3.3 Simulates the process based on acquired data.
 - 3.4 Interacts with LoRa gateway to upload simulation to the cloud and feedback will be sent to the manufacturing system.
4. Data will be analysed on the Cloud then sent as reports to quality control inspection.
5. Cloud can query any data from the nodes such as (conditions of the machine, maintenance issue, etc.)
6. Deep learning works to estimate the maintenance issues and the capacity of production at certain time and quality inspection for raw materials and product.

B. Plug and Play approach

This model is built according to the Reference Architectural Model of Industry 4.0 (RAMI 4.0), see Figure 7. RAMI 4.0 describes the hierarchical levels of a manufacturing system networked via the Internet, the lifecycle of systems and products, and the IT structure of the Industry 4.0 components. The hierarchical levels are almost the same as the layers of the pyramid of automation.

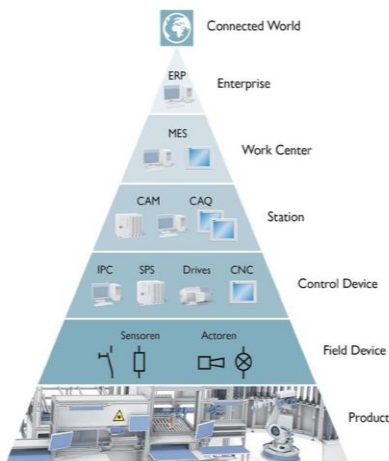


Figure 7: Industry 4.0 productive process pyramid

There is a wide range of commercial brands available in the industrial market that can be utilised to implement an Industry 4.0 approach; these include Siemens, Allen Bradley, Mitsubishi, Omron, Schneider, GE Fanuc, Beckhoff, Moeller, Hitachi, ABB, Phoenix, and Bosch- Rexroth. However, it would be very difficult to construct a generic model for each brand. In this implementation, specific brands are proposed because of their compatibility, availability and market share. In particular, Siemens and Beckhoff, as the big brand names, have been chosen in building our approach to Industry 4.0.

1- The proposed model starts by linking the physical world with the virtual world, the so-called CPS, to monitor the manufacturing processes, and the collected information will be processed using big data analytics. To achieve this step, two hardware solutions are proposed:

A. Siemens SIMATIC IOT2000 which can facilitate data processing/exchange between the manufacturing system and cloud-based data.

B. Beckhoff EK9160 IoT Bus Coupler offers a plug and play module that can simply transmit all control data to all common cloud systems, in a timely and cost effective manner. This allows I/O data to be parameterised via an easy-to-configure website on the device, for sending to a cloud server.

2- For Additive manufacturing, it is recommended to add motion and axis control option for the 3D printer. To achieve this step, two hardware solutions are proposed:

A. Siemens SIMOTION, which provides high-end motion control system, features optimal performance for all machine concepts as well as maximum modularity.

B. Beckhoff CX2040 motion control system will give high-performance and can be used for interpolating 3-D path movements.

3- To perform an integration between the manufacturing data of the physical systems and ERP;

A. The MindSphere Siemens Cloud is a cloud-based IoT operating system that will connect products, machines and systems to interface with the ERP system and will perform any required exchange of data between automated components. The system uses the SAP S/4HANA open cloud platform enabling users to operate, extend and develop the applications in the cloud.

B. The Beckhoff EK9160 coupler will support most of the main cloud systems; Amazon Web Services (AWS), Microsoft Azure and SAP HANA. It will also support the private cloud systems included in many company networks.

4- To enable Physical systems to interact with the real world, particularly to allow for real time simulation and visualisation of the manufacturing process:

A. Siemens provides software, entitled; “SEMATIC inside TIA portal” supports real time visualisation and simulation for manufacturing processes. In addition, NX software offers real time visualisation and sophisticated depiction which is a valuable asset for the product development process.

B. Beckhoff TwinCAT3 supports real time visualisations of the manufacturing process for HMI and Web processing. It allows for analysis, visualisation, diagnosis and recording of variables both external and internal.

5- Finally, CPSs need to increase their experience of utilising machine learning and data mining algorithms.

A. MindSphere Siemens Cloud offers its MindConnect Library on edge devices; providing secure advanced analytics in close proximity to the equipment. MindConnect is suitable for use with descriptive, prescriptive, diagnostic and predictive analytics. Cloud connectivity can be enhanced by combining MindConnect with edge applications in integrated software/hardware environments.

B. Beckhoff TwinCAT Analytics, is able to store process data for each cycle synchronously, this can be invaluable for easy and informative analyses of the processes involved. The software can be expanded with C/C++ and MATLAB for enhancing the analytics application via Mathworks toolboxes for machine learning and optimisation.

Figure 8 summarises the proposed approaches to the practical implementation of Industry 4.0.

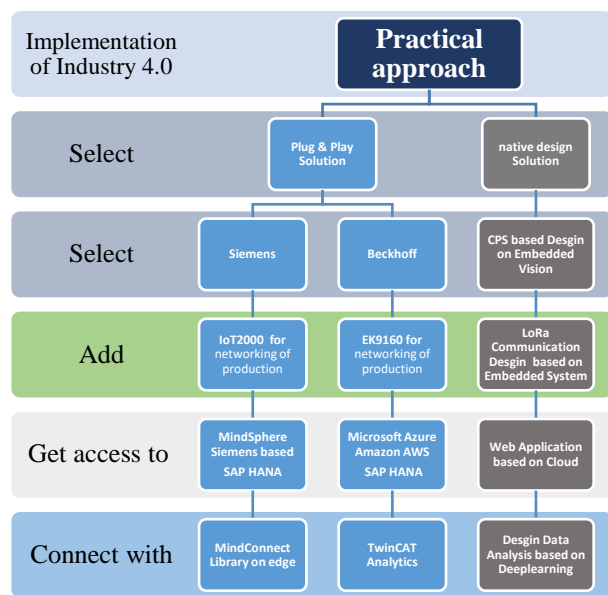


Figure 8: Native approach vs. Plug and Play approach

V. CONCLUSIONS

This paper has presented practical approaches to implant Industry 4.0 in the additive manufacturing process to increase the flexibility, competitiveness and profitability of the manufacturing systems. However, it is also proposing new ways of human machinery interaction. Next step comprises an implementation of M2M communication for Additive manufacturing. Moreover, RFID will be utilised to manage an interaction between machine and product/raw material.

ACKNOWLEDGMENT

The authors would like to thank the European Commission for funding the PAM² project under H2020-MSCA-ITN-2016 Program, Grant Agreement No 721383.

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