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BDA-enabler Architecture Based on Cloud Manufacturing: the Case of Chemical Industry

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Abstract

With the advent of cloud manufacturing (CM), alongside the maturity of specific development approaches and systems in the manufacturing industry, has led to the integration of these initiatives into Industry 4.0 to achieve higher performance. In fact, the implementation of Industry 4.0 is a real opportunity for the process industry around the world which is only at the very beginning of its deployment. However, the integration of cloud manufacturing requires the fully digitalization of industrial systems and the implementation of big data management process. Indeed, the lack of resources to handle the huge flows of data in transit and the lack of standards and interoperability is the biggest challenge to the large-scale adoption of smart manufacturing. To get around this problem, it is necessary to put in place management and analysis solutions for big data to facilitate data acquisition, process monitoring, anomaly detection and predictive and proactive maintenance. In addition, the implementation of a smart manufacturing architecture based on big data analytics (BDA) requires a lot of resources in terms of storage and computing power, which is not always available in an industrial context. Thus, it has become essential to offer suitable manufacturing models for the implementation of big data analysis services that meet the new requirements of the manufacturing sector. In this paper, a case study in one of the main African Phosphates Company will be presented. Thus, we will propose a BDA-enabler architecture based on Cloud manufacturing to identified digital opportunities and key benefits regarding performance management, production control and maintenance. The findings will help manufacturer to understand cloud manufacturing and big data analytics capabilities and take advantages from their potential and their digital opportunities to assess manufacturing process.

Keywords: Big data analytics; Cloud manufacturing; Industry 4.0; Case study; Predictive manufacturing; Production control; Maintenance and performance management.

1. **Introduction**

The manufacturing industry plays a key role in the development of countries and the world economy. In recent years, the industry in general and the manufacturing industry in a specific way have grown exponentially with the emergence and use of new technologies such as Cloud Computing, Big Data and the Internet of Things (Hopkins and Hawking 2018). This phenomenal growth has created a smarter, more autonomous industrial era called Industry 4.0 (Dremel et al. 2020). The manufacturing industry includes the processing industries and the repair and installation of industrial equipment. The manufacturing industry includes among others textile manufacturing; the industry of computer, electronic and optical products; automobile industry and the chemical industry. The manufacturing industry meets several issues such as complex product design, high energy consumption, and the transition need from production-oriented manufacturing to service-oriented manufacturing (Derigent and Trentesaux 2020).

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To meet these challenges and issues, companies are trying to develop modern and smart manufacturing strategies and models, which would allow them to have a faster time to market, a higher quality, a highly competitive cost, greater flexibility, and better services (Bahrami and Singhal 2015; Upadhyay and Sharma 2021; Bag et al. 2021) . The implementation of these manufacturing models must take into consideration the company's requirements in terms of flexibility, agility, and scalability to improve production efficiency and to maintain competitiveness.

To work around this problem and to support the integration of smart manufacturing, the use of the big data analytic (BDA) techniques has become a necessity for data acquisition (data acquisition of different sensors and existing homogeneous or heterogeneous database), process monitoring, anomaly detection, anomaly analysis and predictive and proactive maintenance. However, implementation of big data analysis architecture requires a lot of resources in terms of storage and computing power, which is not always available in an industrial context. Thus, it has become essential to propose adequate manufacturing models for the implementation of big data analytics services that respect the new requirements of the manufacturing sector. To meet the needs of manufacturing industry in terms of resources and in analysis and improvement of production, Cloud Manufacturing was introduced in 2010. The main idea of Cloud Manufacturing lies in the providing all types of manufacturing resources as a service, while connecting companies with cloud resource providers, to respond to their needs throughout the product development cycle.

In general, the use of cloud manufacturing based on big data analytics (BDA) technologies in an industrial context can offers several opportunities for manufacturing processes. However, relatively few companies take full advantage of BDA potential. In fact, despite the various advantages of the BDA in the industrial fields, its deployment remains very limited because there is no clear documentation that accompanies the good practices of unstacking and which groups the capacities in terms of performance according to each context, and each use cases.

The purpose of this paper is to propose flexible architectures using big data analytics in a cloud manufacturing environment to process, manage and analyze data collected from different databases and sensors in companies. This data will serve as a basis for the implementation of a Smart Manufacturing System and deploying continuous improvement tools such as lean toolbox, statistical process control and professional maintenance. In this context we will conduct an explicit study in one of the main manufacturing Company in North-Africa and we detail and analyses the obtained results when applying a BDA-enabler architecture based on Cloud manufacturing. Furthermore, we will explicit the identified digital opportunities for performance management, production control and maintenance and then we will perform a sensitive analysis to extract the key benefits of integrating BDA on Cloud manufacturing-based architecture.

This paper is organized as follows: in section II we present some theoretical background concerning the cloud computing and the cloud manufacturing and its potential application for the advancement of big data analytics in the manufacturing process. In section III we present a systematic literature review to extract the potential benefits and challenges of using cloud manufacturing as a leverage of BDA in manufacturing process. Section IV aims to describe the proposed conceptual architecture based on cloud manufacturing to enable the use of BDA in manufacturing process with the technologies required. In section V we propose an implementation of the proposed architecture in the case of chemical industry and then we conclude the paper.

2. Related work and research scopes

2.1. Challenge of Cloud Manufacturing adoption

Cloud manufacturing is a process used to enable ubiquitous, convenient, on-demand network access to shared pools of configurable manufacturing resources. These shared pools can rapidly configure and release networks, servers, and storage through minimal management effort or service provider interaction. This way, the information can be viewed, updated, and applied at any time or place (Mohamed 2018). Cloud manufacturing can be very beneficial to manufacturers. One of its advantages is that companies' IT teams don't have to deal with software maintenance, including technical support, hardware/software maintenance and security (Mor et al. 2020). In fact, the cloud speeds up the process by automating the communication between manufacturing and accounting. It can reduce capital expenditures, as cloud computing eliminates in term of the significant long-term costs that occur in traditional enterprise resource planning (ERP) systems.

The current challenges of promoting and applying manufacturing network model are how to share more manufacturing resources, and capabilities in a wider range, realize barrier-free transaction and circulation of manufacturing resource and services heterogeneity, Complexity of Network environments, virtualization issues, scalability and Security concerns (Khan et al. 2021). Robert henzel and al. (Henzel and Herzwurm 2018) presents a survey of current challenges issues of deploying Cloud Manufacturing and discuss the main research publication in this field. In their paper, they present the main concepts and key characteristics of building CM architectures such as used services, Networked environment, virtualization, scalability and Security (Zkik et al. 2019; Sebbar et al. 2020). The authors propose also a classification of current research depending of their main contribution and discuss works that deal with data security and trust (Lu and Xu

2019), development of a Business Model for CM (Ren et al. 2019), Systems and services integration in CM (JunPing Wang et al. 2018) and implementation of big data analytics process (Belhadi et al. 2020). Yongkui Liu and al. (Liu, Wang, and Vincent Wang 2018) discuss the latest advancements in Cloud manufacturing and present some of his future directions and perspectives. To do so, authors discuss first different concepts of CM and present his architecture and services and present the Cloud Manufacturing as a new technology that includes several concepts and principles such as big data and machine learning (Lu and Xu 2019), 3D printing (Chun, Kim, and Lee 2019), robotics and artificial intelligence (Reddy and Shyam 2020), production (Xu 2012), maintenance (Henzel and Herzwurm 2018), trust and security (Wang, and Vincent 2018).

2.2. Big data analytics for manufacturing

Big data analytics is a method of using tools and processes to gain insights from large volumes of data. This data has one of three characteristics: large capacity, high speed, or extreme variety. Big data analytics aims to draw correlations and conclusions from data that was previously difficult to understand by traditional tools such as spreadsheets. Big data analytics helps in providing business intelligence that can reduce costs and improve the efficiency of operations. It's can analyze past data in order to make predictions about the future and improved decision making. Businesses can analyze past data about product launches and customer feedbacks to launch better products in future (Mishra, Upadhyay, and Sharma 2021a; Junliang Wang et al. 2021). The biggest challenge in using big data analysis is to segment the useful data in the cluster. The data required for analysis is a combination of organized and unorganized data, which is difficult to understand. There are as many uses of big data analytics as there are opportunities. Big data that fully utilizes its functions can produce revolutionary changes in the world, and it can even be said to be as big a change as the Internet. Stefan Windmann and al. (Windmann et al. 2015) discuss the implementation of big data analytics technics in all steps of a manufacturing process which includes data processing, data acquisition, assistance system and ends user interactions. To do so, authors choose three industrial areas to make their analysis and investigation on anomaly detection algorithms which are chemical industry, mobile agricultural harvesters, and sorting plants industry. Authors present also several model-based and data-driven anomaly detection algorithms such as Distance based approaches, Regression models, Self-organizing maps and PCA-based anomaly detection. This work proof the necessity of using big data analytics technics in manufacturing context but it do not discuss the different challenges and issues when their deployment. In other hands, Xun Xu (Xu 2012) discus features of cloud as one of the major enablers for the manufacturing industry and the migration from cloud computing to cloud manufacturing. In their paper author mention the main feature of using CM and present the main research contributions (Karim et al. 2016; Kumar and al 2021) to the concept of cloud manufacturing .

2.3. Cloud Manufacturing based on Big data analytics

The implementation of Cloud Manufacturing and the use of big data analytics techniques allow companies to benefit from several services and increase their efficiency and productivity. In this context, several research studies have focused on improving production and designing new and efficient production models using CM and BDA algorithms. Brecher, et al. (Lohse, and Vitr 2009) recognized that applications in an information-intensive manufacturing environment can be organized in a service-oriented way using CM architecture. The approach is called "Open Computer Manufacturing" (openCBM) in support of cooperative process planning. The goal is to reduce the negative impact of software homogeneity issues along the production chain. Vander Velde (Velde 2009) presented a plug-and-play framework for building modular simulation software to create a run-time configuration integration environment for engineering simulations in CM context. Nessehi et al. (Nassehi et al. 2008) proposed a framework to solve the problem of incompatibility between CAx systems (Nassehi et al. 2008). Their framework provides an industrial infrastructure as a service platform using cloud computing features to provides individual interfaces for different production systems.

Several case studies (Henzel and Herzwurm 2018) were also conducted to prove the usefulness of using cloud computing services in an industrial context. Keng-Boon Ooi et al. (Ooi et al. 2018) conducted a case study in Malaysia which proof the effectiveness of using cloud computing in manufacturing enterprises and his applicability. For that, authors analyses performance expectancy, firm size, and absorptive capacity of several firms in Malaysia while using cloud computing services. Authors conclude that using Cloud Computing can significantly increase innovativeness and performance and promotes the evolution into smart and 4.0 industry. In their investigation, authors use several big data analytics technics to analyses gathered data such as Partial Least Squares, Structural Equation Modeling analysis and Artificial Neural Network analysis.

Despite the significant results from these various research projects, several points have not yet been addressed, especially when using the Big Data Analytics architecture for manufacturing process. The most important point is to know the real impact of using CM and what are the practical requirements that must be arranged and what are the different challenges that need to be addressed. However, the lack of standards and a clear methodology for the implementation of CM and BDA in an industrial context leaves companies cautious and very unenthusiastic to migrate to these technologies. To answer these different issues, we will focus on this work on the response of several research questions specific to this topic:

- QR1: What is the optimal solution for storing, editing, retrieving, analyzing, maintaining, and recovering big data?
- QR2: How can cloud Manufacturing help in handling big data issues?
- QR3: How to build a real architecture based on the use of Cloud Manufacturing without interfering with the quality and efficiency of production?
- QR4: How can BDA-enabler architecture based on cloud Manufacturing help in the improvement of performance management, production control and maintenance?

3. Implementation of the proposed BDA-enabler architecture based on Cloud manufacturing: the case of chemical industry.

3.1. Background and context

The main purpose of our work is to study and identify digital opportunities when setting up a BDA-enabler architecture based on Cloud manufacturing. In this context we conducted a context-specific study in one of the main African Phosphates Company. For confidentiality reasons, the name of the company will not be disclosed, and we will use the name AFP as a pseudonym. In this study we will:

- Present the initial state of the digital infrastructure and we will detail the identified problems.
- Present the proposed BDA-enabler architecture and we will discuss the different modules put in places.
- Detail the results obtained when applying this architecture.
- Discuss identified digital opportunities regarding performance management, production control and maintenance.
- Present the different lessons learned from the case study.

AFP is a leading chemical company and one of the largest manufacturers of phosphates and its derivatives in North Africa. The company is responsible for managing the large phosphate reserves in the North African country and produces a number of by-products such as phosphoric acid, animal feed and fertilizers. AFP has set up an industrial transformation program with a total cost of 20 billion dollars to strengthen its industrial capacity and improve the quality of these services and increase its efficiency. To support this large-scale program, it was essential to improve the company's IT infrastructure and implement a robust architecture capable of managing the increase in production and processed data. As a result, different parts of the company have taken advantage of the industrial program to integrate the scanning component into the various manufacturing processes. The main goal of this study is to identify opportunities when using CM in order to improve performance management, maintenance and production. First of all, we will present the initial state of the digital infrastructure of AFP and we will explain the different part and existing IT platforms.

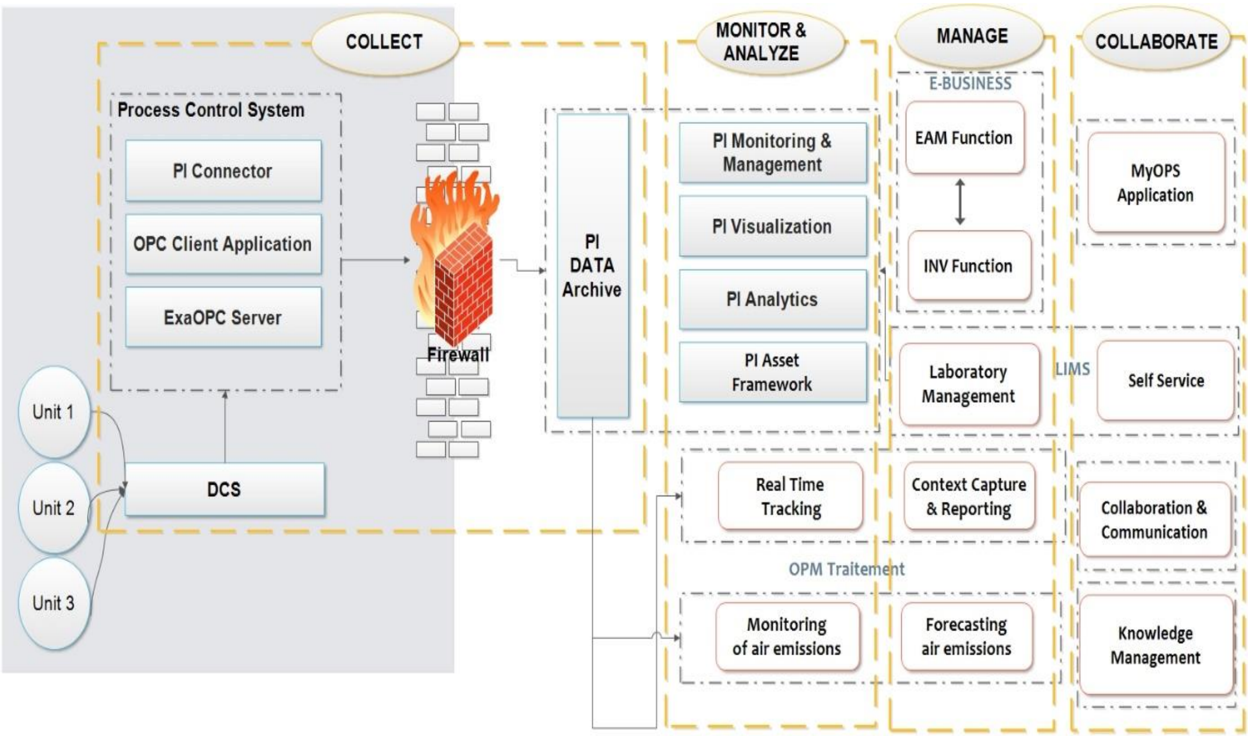

Figure 1. Different components of the initial architecture

As shown in figure 1 the architecture is composed by 4 distinct parts: Data collection, Monitoring and data analysis, Management plane and Collaborating system. The different components of our architecture are detailed on table 1.

Table 1. Describe the main components of our initial architecture

	Component	**Definition**
Data collection plane	PI connector	Is a key element of process control system that collects information from targets and data sources. Pi connector checks the structure and automatically create for each PI Points, AF features accordingly and AF Elements.
	OPC Connector	Duplicates contextual information and time-series data from data archive servers.
	Exa OPC	Store diverse data regard for one year for regulating and processing data
	DCS distributed control system	Responsible of collecting data from different locations PI Vision users accessing PI System data.
	Firewall system	FW systems are built to filter traffic between industrial and enterprise based on intelligence aspect, source and destination IP & ports and monitoring abnormality.
	Pi Data Archive	Pi data archive or backup is a copy of data archived in real time, which can be used in the logs and events that the original data is damaged or lost. After accidental configuration changes (such as accidental deletion of points) and database corruption, backups provide a way to recover.
Monitoring and data analysis plane	PI events and Notification	Gives the PI stores data and the data archive as events, which is each event has a time-stamp and a value that gives the collection time of the value. Pi notification service to note warning or update recommended.
	PI Analytics	Analyze information based on performs calculation and scheduling its executions (e.g: number of active users so that I am aware of the user engagement). This analysis takes values from OPC client application as inputs to produce new outputs, new events, event frame.
	PI visualisation	Pour visualiser les données collectées et stockées, les utilisateurs se servent d'outils
	PI asset framework	Server is one method of accessing the PI Data Archive server, and there may be other PI and non-PI servers. Users request data from the PI AF Server or PI Data Archive for display in the client tools.
	Real time tracking	Real time is best stored in a database that allows for fast storage, fast retrieval and automatic compression such as the PI Data Archive.
	Monitoring and air emission	Slow changing or static data may be better stored in relational databases structures, or the asset centric elements found in the PI Asset Framework (PI AF) database.
Management plane	Oracle EAM	Oracle Enterprise Asset Management (eAM) used to create and implement maintenance procedures for both assets and rebuildable inventory items
	Oracle INV	Oracle Inventory provides several predefined item types,
	Laboratory management	used to administer the PI Data Archive servers from client connections.
	Context capture and management	The PI System Manager Tools install kit is included with every PI Data Archive server and is available as a separate download. The PI System Management Tool kit includes the following programs.
	Forecasting air emission	Predicting the composition of the air in the atmosphere for a given location and time.
Collaboration Plane	MyOPS	deployed as a tool for the HSE processes and the maintenance reliability
	Collaboration and communication	Enabling communication between the Control Network PI System and the Corporate Network PI System
	Knowledge management	The knowledge gained to set up the PI interfaces in order to create predefined PI and verify the management setup.

The first part of the architecture is responsible of collecting data from the existing data base scattered in different industrial sites and it represent the data collection plane. The main component of this plane is the distributed control system (DCS) which is responsible of collecting data from different locations and store it for almost one year and for regulating and processing data. DCS is also considered as a communication system that ensures communication between the different IT system equipment especially between computers, automata and controllers. DCS is directly connected to the Process Control system (OPC) which allows communication between different types and brands of PLCs and ensures system homogeneity and interoperability between different software and hardware manufacturers.

The second part is responsible of monitoring and analyzing data gathered and stored from the data collection Plane and it represent the monitoring and data analysis plane. To ensure the connection between data collection plane and the monitoring and data analysis plane a highly scalable and transforming operational data PI system is set up. PI system is used as self-service monitoring capability of data by using process engineer. It permits to capture, and archive collected data and getting the right data at the right time to the right person or machine. Gathered data is centralized on PI data archive before being monitored and analyzed by the other components of the PI system. The main component of the PI system is the PI server which permits to transforms datasets into actionable information and samples and makes it accessible and to monitor and deliver real-time alerts in case of failures or when a critical event occur. In order to group, categorize and analyze information issued from PI systems a real time tracking and air emissions platforms were set up. The real time tracking platforms permit to store alerts and analyze them to resolve failures detected instantly and to avoid them in the future. Considering the production nature of the AFP company, monitoring and limiting air emission is essential to ensure safety and quality. To do so, monitoring of air emissions platform is directly connected to the PI system to analyze emission values gathered from industrial collectors and nodes. The third part represents the management plane which is responsible of the management of industrial operations; ensure coordination between all components of the architecture and managing tasks and anomalies. The management plan works at three main levels:

- Performance management: Considering performance management an OPM treatment system is used as a tool of performance monitoring. OPM treatment system is directly connected to real time tracking by a context capture and reporting platform to manage real time alerts and provide suitable actions of each entry. OPM treatment system is also responsible of forecasting air emission based on data issued from monitoring of air emissions platform to enhance performance and decrease risks.
- Production control and information management: In order to enhance production and manage information at all levels of IT infrastructure a laboratory information management system (LIMS) is used to allows to effectively manage the flow of samples and associated data to improve lab efficiency through standardizing workflows, tests and procedures, while providing accurate controls of the process.
- Maintenance management: In order to manage, track and facilitate tasks and activities with a single view of the overall performance Oracle EAM platform is used. This platform addresses the comprehensive and routine asset maintenance requirements of asset intensive organizations, measure performance in a single view, and repository with self-service applications and switch from a reactive maintenance mode to a preventive maintenance according to conditions.

The fourth part represents the collaboration plane which permits to improve collaboration and drive action-oriented tasks and reporting between different units and industrial sites. This plan permits to offer a sharing knowledge environment to enhance productivity and to minimize business risks within the company by implementing suitable procedures to ensure the preservation of health, safety, and environment (HSE). To do so, MyOPS platform is already deployed as a tool for the HSE processes and the maintenance reliability. Collaboration & communication and knowledge Management Platforms are also used at the level of collaboration plane for sharing expertise and they constitute an information space where people are interlinked to their knowledge by applying the principle of Internet of People (IoP).

3.2. Limitations of the initial architecture

The objective of this section is to give an overview of the limits of the initial architecture. Thus, we will describe the gaps and the limiting assumptions underlying the different components. Thus, we critically examine the assumptions and discuss the limitations of the prevalent state-based architecture-based analysis techniques. Furthermore, we will provide a brief discussion of how these identified limitations can be addressed. These limits derive from the initial architecture described in the previous section. We have decomposed these limitations into eight vectors to facilitate their analysis as shown on figure 2. These vectors are presented as follows:

A. The OPC server which ensure communication between all controllers and machines is deployed in windows machine which present a high-level security risk.
B. Due to lack of Lora network at the level of all units and industrial sites, the data issued from smart sensors are not exploited.
C. To analyze data gathered from sensors at the level of all units, we should dispose of a data warehousing area with a huge storage and archiving capacities. However, the storage capacity of the existing DSC server historical data is limited to 1 month which is not enough at all.
D. PI Visualization is used as self-service monitoring capability of data Plant by Process Engineer and do not interact with the other platforms of the architecture.
E. MyOPS platform is already deployed as a mandatory tool for the HSE processes, and the maintenance reliability processes which are defined by the Operational Excellence team but it must be implemented on each industrial site separately.
F. The capability of monitoring Data Plant is provided only by PI Visualization and real time tracking which is not enough.
G. The performance as well as the user experience offered by OPM, and especially at the level of context capture and reporting platform, are not optimal and they are subject to redesign.

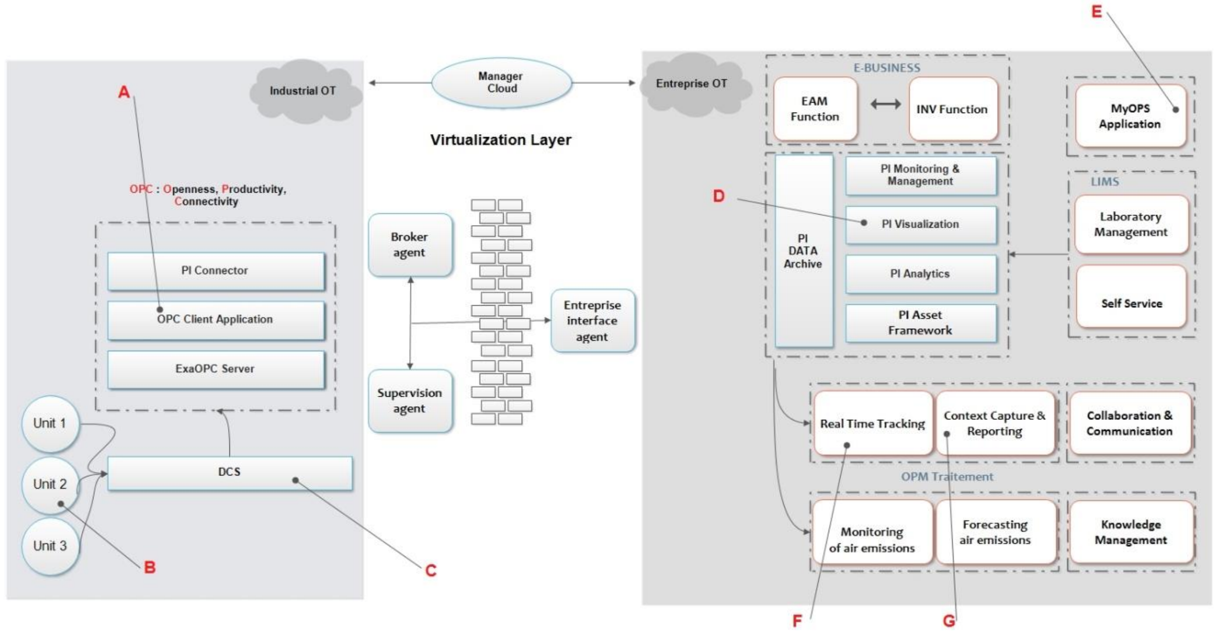

Figure 2. Limitations of the initial architecture

The conception of a fully digitalized and cloud manufacturing-based architecture will face many challenges in key enabling technologies and concepts. Besides the use of smart sensors represents one of the pillars of the implementation of industry 4.0 and smart manufactory and the integration technologies of Cloud computing, IoT, and embedded systems arise several important technical issues such as security and privacy. Furthermore, big data management represent a real challenge for this architecture. Thus, enhancing stockage capabilities and providing a collaborative architecture to manage data become mandatory. In the other hands, data analysis should be more proactive and able to detect anomalies more quickly to improve performance management, production control and maintenance.

3.3. Cloud Manufacturing based on BDA proposed architecture

To respond to these limitations of the initial architecture we propose in this section a new architecture which present cloud manufacturing based on big data analytics based on new key elements. To improve performance management, maintenance and production based on the advantages of CM-BDA; we propose new module to increase the monitoring of the chemical industry system as shown in figure 3.

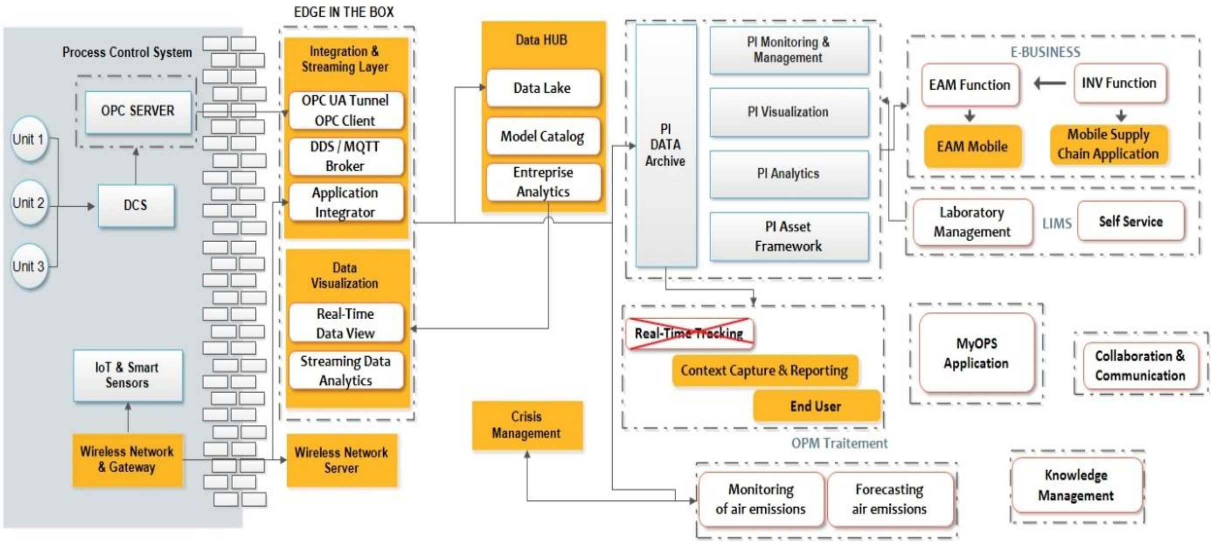

Figure 3. End-state MC-BDA architecture

The different components of the new platform are presented as follow:

- The real-time tracking permits the reporting and the analyses of the gathering data from different sources by reducing manual input. Thus, we enable the tracking and transparency of production, that empower teams to provide a global overview of the plant performances through the effective reporting.
- The Oracle Enterprise Asset Management and inventory report, we add successively the oracle EAM mobile and the mobile supply chain application. the oracle EAM mobile present the daily work management which improve interaction between production and maintenance with efficient tracking of request, raising work orders and capturing feedbacks.
- The Myops platform, improve the maintenance reliability processes. Thus, we add new predefine process as known efficiency of daily meetings, improving shift handovers, spotting and escalation of anomalies and validation of anomalies' resolution.
- The OPC server is connected to OPC client through OPC UA tunnel included which is add to new component called EDGE in the BOX. The aim of the edge in the box is to design & build IT/OT architecture to cover all data needs for the industrial pilot and beyond.
- The data hub module is present the data lake, the different model catalog, and the enterprise analytics. This module helps edge box in real time visualization by building the different information from it and operating it via application integrator. In this regard, present reliability of our system by archive history (PI data) of the upskilling to predict the maintenance and prepared it for potential leakages, risks and breakdowns. In the same hand is connected to the OPM treatment to monitor and to forecast air emissions
- The collaboration & communication module illustrate the production enablers as knowledge management upskilling, communication, transportation logistics. These components enable maintenance to manage, track and facilitate tasks and activities with a single view of the overall performance.

The aim of the proposed framework is to improve the performance management, production control and maintenance in the realm of the use of big analytics tools. Table 2 describes the main identified digital opportunities an each of these pillars while implementing the proposed architecture.

Table2. Digital opportunities identified in the CM-BDA key elements

Key elements	Digital opportunities identified	Description
Performance Management	Consolidation of performance indicators	Create an efficient way of gathering data from different sources by reducing manual input
	Efficiency of daily meetings	Use the daily meetings to improve collaboration and drive action-oriented tasks and reporting
	Reporting of performance indicators	Empower teams by providing them a global overview of the plant performance through effective reporting
Production Control	Improving shift handovers	Consolidate effectively activities to help teams have a handover that is informative, seamless and effective
	Spotting and escalation of anomalies	Improve the efficiency of reporting anomalies through standardised procedures for effective resolution and transparency
	Validation of anomalies' resolution	Empower experts to validate anomalies quickly by providing transparency of equipment functioning
	Traceability on fertilizers sold	Enable tracking and transparency of fertilizers production to improve customer interaction and experience
	Production enablers (knowledge upskilling, communication, transportation logistics)	Enable staff to manage production better by connecting employees with experts and improving efficiency across key touchpoints like logistics and communication
Maintenance	Reliability	Be predictive in the way maintenance is conducted to be prepared for potential leakages, risks and breakdowns
	Spare parts and purchasing	Allow for better planning of maintenance by providing visibility of stock and enable easy purchase
	Daily work management	Improve interaction between production and maintenance with efficient tracking of request, raising work orders and capturing feedback
	Shut-downs Management	Create transparency in the way shut-downs are managed and resolved
	Maintenance Performance Management	Enable maintenance to manage, track and faciliate tasks and activities with a single view of the overall performance

As shown in table 2, the implementation of the proposed architecture permit to identified several digital opportunities that may foster the implementation of a fully digitalized and smart manufacturing architecture. The analysis of the results allowed us to identify three crucial development points, namely the consolidation of performance indicators, efficiency of daily meetings and escalation of KPI.

Consolidation of performance indicators:

- Automatic consolidation of relevant performance data from DCS.
- Automatic calculation of KPIs with the ability to flag inconsistencies and manually validate data.
- Automatic consolidation of all performance data and KPIs into one tool.
- Increase of storage capacity of DSC historical data.
- Real-time recording and diffusion of laboratory values within the system.

Efficiency of daily meetings:

- Digital dashboard allowing to discuss performance during morning meeting.
- Application linked to dashboard allowing to interact with different screens.
- Connection between daily meeting dashboard and existing tools to enable visibility on day-to-day tasks.

Escalation of KPI:

- Dashboard in the control room permit track real time performance of the unit vs. targets.
- Automatic generation of reports adapted to different stakeholders.

In summary, we conclude that the implementation of BDA-enabler architecture offers several opportunities by integrating BDA capabilities. The case study also highlights the specific actions that AFP has taken concerning each mechanism at the level of structure and technology to allow the implementation of a fully smart and digital system based on cloud manufacturing.

4. Results of the application of BDA-enabler architecture based on Cloud manufacturing

We conducted a study at AFP one of the main African Phosphates Company, to investigate the use of BDA in order to foster cloud manufacturing-based architecture, which was identified as lacking in research base. We have identified three development keys for BDA based architecture pillars, namely: 1) Production control, 2) Maintenance and 3) Performance Management, and we have detailed the keys benefits for each level as shown in table 3.

In fact, the application of BDA-enabler architecture based on cloud manufacturing prove good result enhance CM-BDA key pillars known as production control, performance management and maintenance. In fact, the proposed architecture permit to ease production control operation and permit to optimize spots, escalates, and cover the resolution of anomalies, and improving shift handover. Furthermore, the obtained results permit to enhance the efficiency of performance management on term to effectiveness of daily meetings, consolidation, and reporting of performance indicators. Finally, the CM-BDA permit to enhance the efficiency of maintenance operation and offer a better system reliability while facilitating purchasing operations by using different tracking techniques, managing various maintenance applications, and displaying real-time during shut-downs.

Table 3. CM-BDA key pillars and benefits

<table>
<tr><th>CM-BDA key pillars</th><th>Key benefits</th><th>Description</th></tr>
<tr><td rowspan="3">Production control</td><td>Improving shift handovers</td><td>▪ Tool allowing for consolidation of recorded information with automatic generation of a report at the end of each shift / day
▪ Company email address for all operators to see the online contents and receive reports</td></tr>
<tr><td>Spotting and escalation of anomalies</td><td>▪ Different warning sounds in control room depending on criticalness of issues.
▪ Notifying operators of patrol plan with access to SOPs
▪ Voice functionality on app allowing illiterate people to record key observations.
▪ Provide a checklist for the operator to conduct patrols and update the status of controls by adding comments
▪ Broadcasting software allowing remote access to process cameras outside of control room
▪ Application to launch intervention requests a smartphone</td></tr>
<tr><td>Resolution of anomalies</td><td>▪ System allowing production managers to validate remotely the completed maintenance interventions through pictures/videos
▪ Application showing a status of equipment functioning (i.e., key indicators, consignment status)</td></tr>
</table>

Table 3. Continued

CM-BDA key pillars	Key benefits	Description
Maintenance	Reliability	▪ System linked to Advanced Analytics models to spot equipment dysfunctions (e.g., faulty sensors) ▪ System allowing to remotely pilot electronic mouse to detect ammonia leaks. ▪ Lack of capacity to consolidate cross category/site data and demands
	Purchasing	▪ Application tracking spare parts orders and identifying delays ▪ System connected to Oracle to track and report the exit of equipment ▪ Electronic signature for goods issue documents ▪ Automatic launch of procurement requests based on inventory levels ▪ Dashboard tracking in real time the consumption and storage of oil and grease - with push notifications to purchasing department ▪ Application reading the barcodes/QR Codes in order to identify equipment and have access to inventory levels
	Work Management	▪ Application linking maintenance to production - allowing to digitally validate work orders ▪ Application allowing an automatic generation of intervention requests based on the sensor's values. ▪ System generating maintenance planning based on intervention requests and values displayed by sensors ▪ Tool allowing for an automatic generation and update of the maintenance criticality matrix ▪ Application allowing to track in real time MTBF and previous interventions of any equipment ▪ Mobile application notifying any incident/accident/danger in the plant ▪ Application allowing to manipulate UAVs (drone) for oiling and greasing of equipment at height ▪ Application digitalizing oiling and greasing checklist ▪ Application allowing maintenance operators to influence maintenance planning by providing feedback ▪ Shared platform with contractors allowing to facilitate and fluidify collaboration ▪ Application providing access to the number of RSAs and solutions defined / implemented ▪ Application on smartphone allowing to view surrounding equipment and specific safety equipment required ▪ Dashboard tracking the completion status of maintenance interventions
	Shut-downs Management	▪ System displaying data in real-time during shut-downs ▪ Application calculating durations between interventions
Performance Management	Consolidation of performance indicators	▪ Dashboard for maintenance performance management ▪ Huge capacity of storage and consolidation of more than 89 000 parameters with an historic of more than 1 year ▪ More than 2 500 parameters gathered and consolidated in a global KPI's and performance report by less than 5 min ▪ Huge share capacity of more than 15 000 accounts
	Efficiency of daily meetings	▪ Capacity to store historical data from 6 OPC and more than 89 000 for up to one year ▪ Visibility and monitoring of the DAs for the maintenance preparator ▪ Automation of store entrances and exits (PdR, Interchangeable) to improve warehouse stock reliability and productivity
	Reporting of performance indicators	▪ Generation of consolidated report instantaneously ▪ Storage of key observations ▪ Huge capacity of videos storage to up to 1 year ▪ Efficient connection between production and maintenance departement

5. Discussion & Implications

Cloud manufacturing can maintain the competitiveness of enterprises by providing many advantages such as cost efficiency, resource pools, rapid flexibility, and easy management. However, the implementation and the deployment of such technology present many challenges especially in terms of data storage and management, data analysis, performance, privacy, and security. The use of big data analytics technologies as key pilar of cloud computing will enable companies to make proactive and knowledge-based decisions, as they will enable them to predict future trends and behaviors. Thus, businesses will be able to store and analyze their data remotely and to access their services anytime and anywhere.

The aim of this study was to propose a flexible architecture using big data analysis in a cloud manufacturing environment to process, manage and analyze the data collected from different databases and sensors in enterprises. This data will serve as the basis for the implementation of an intelligent manufacturing system and the deployment of continuous improvement tools, statistical process control, and professional maintenance. Furthermore, we conduct a case study to identify digital opportunities of the proposed BDA-enabler architecture based on Cloud manufacturing for performance management, production control, and maintenance. In addition, we perform sensitivity analysis to extract the main benefits of integrating BDA into a cloud manufacturing architecture. It is noteworthy that our paper is the first that combines a systematic literature review with a case study to offer a holistic overview regarding implementing BDA-enabler architecture based on Cloud manufacturing in manufacturing process.

The present work bears some interesting insights for theoretical and practical implications of using BDA based on cloud manufacturing architecture. In fact, the findings can aid academic researchers to tackle new empirical research in this field and clear up BDA and cloud manufacturing concepts. Furthermore, this paper regroups the main BDA and cloud manufacturing challenges, based on obtained results from literature review and the conducted case study. In the other hands, this paper has attempted to provide to researchers and managers meaningful knowledge on the implementation of BDA based on cloud manufacturing architectures in the manufacturing process environment. in this regard, this study makes it possible to optimize the availability and performance of management supports and makes it possible to exploit existing resources. It also allows managers to develop new service strategies and new business models. Thus, the proposed case study may help manufacturing companies to transform into fully digitalized smart manufacturing while using BDA and cloud manufacturing as important pillars in industry 4.0 for manufacturing process. The analysis of the case study allowed to leive the main digital opportunities which present some interesting insights for practical implications allowing to make the right decisions to optimize performance management and production control. This finding represents a huge contribution since it provides essential recommendations to consider while building BDA based on cloud manufacturing architecture. In addition, companies operating in similar conditions to AFP can benefit from the findings to design their infrastructure that enable the use of BDA and cloud manufacturing for their manufacturing process.

6. Conclusion

The use of BDAs for big data and manufacturing process management is taking on increased importance on the road to operational excellence. Indeed, manufacturing processes and production tools have undergone enormous changes over time, spurring rapid technological advancements throughout the industry. In this regard, this document proposes a flexible architecture using big data analytics in a cloud manufacturing environment to process, manage and analyze the data collected from different databases and sensors in industrial context. Accordingly, this study begins with a case study that aims to identify the main capabilities and limitations of smart cloud manufacturing architectures. Then, we propose a BDA-enabler architecture based on cloud manufacturing to improve performance management, maintenance, and production control and to bypass the identified limitations on the initial architecture. The proposed architecture offers an optimal solution for storing, editing, retrieving, analyzing, maintaining, and recovering big data as is use both BDA and cloud manufacturing capabilities. To do so, cloud Manufacturing is used to store and asses' data to better handling big data issues without interfering with the quality and efficiency of production. Furthermore, the proposed CM-BDA architecture offer many digital opportunities; these opportunities lead up to several key benefits regarding performance management, production control and predictive maintenance. Thus, BDA-enabler architecture permit to ease production control operation and permit to optimize spots, escalates, and cover the resolution of anomalies, efficiency of performance management on term to effectiveness of daily meetings, consolidation, and reporting of performance indicators.

Future research should focus on the use of quantitative analysis methods to evaluate the impact of BDA capabilities on manufacturing performance, and more in-depth empirical research must be conducted based on main data.

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