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New business and operating models under Industry 4.0 paradigm to boost industrial Process Optimization. Industrial Internet of Things (IIoT) and Artificial Intelligence/Machine Learning (AI/ML)

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ABSTRACT: *This paper pretends to approach and analyse new business and operating models that arises under the Industrial digital paradigm. Known by different names like Industry 4.0, Smart Manufacturing, or Production 4.0, among other terms. Digitalization in industry is advancing at a tremendous speed, and is pushing stablished firms to change and adopt new tools. Besides it opens opportunities to technological startups to deliver new products and services to the industrial market.*

As an example of opportunities in operating models, it is clear that digitalization under the model Industry 4.0 and the advantages of Industrial Internet of the Things (IIoT), allows faster response to customer demands, increase flexibility allowing the adaptability to manufacturing processes, and provides a tremendous amount of tools for quality improvement in the processes, among other advantages.

This article looks into the framework of the adoption of Artificial Intelligence and Machine Learning and its integration with IIoT under industry 4.0 as driver for Industrial Process optimization, and the opportunities to gain more adaptability, productivity, and better quality.

The paper explores some related articles that were find relevant issues regarding the key topics around IIoT and Artificial Intelligence as a value added solution for process optimization under Industry 4.0 paradigm.

At the end the hypothesis regarding the importance of platforms, open innovation, agile change management related to the new business and operating models are somehow solved, and it give visibility to the opportunities that the emerging business and operating model provide to improve processes in the industrial environment.

KEYWORDS: *Industry 4.0, Industrial AI/ML, Data driven management, IIoT, operating and business models.*

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I. INTRODUCTION

This paper pretends to go further from previous work regarding Industry 4.0 paradigm, and the potential for new business and operating models in the installed digital manufacturing scenario according to Walas Mateo & Redchuk, (2021). The proposal for this work is to go deeper into opportunities around solutions on IIoT and Artificial Intelligence/Machine Learning (AI/ML) as process optimization driver in the industrial environment.

Industry 4.0, smart manufacturing, the fourth industrial revolution, or production 4.0, different ways to name the new industrial paradigm, goes beyond the industrial shop floor. It is about overall transformation by means of digital integration and intelligent engineering. It is referred as the next level of manufacturing where ma-chines will redefine themselves in how they communicate and perform individual functions (Muhuri et al. 2019).

To start the discussion of the subject it is being approached, the definition of business operating model and business model by Iansity and Lakani (2020) has to be considered. The authors define that the value of a firm is shaped by these two concepts. The firm's business model, defined as the way the firm promises to create and capture value. The firm's operating model, defined as the way the firm delivers the value to its customers.

Another point to introduce before going into the core concepts for this article is referred to the Cyber Physical Systems (CPS), term that identify systems with integrated computational and physical capabilities that can be interfaced in different ways (Ruiz-Sarmiento et. al, 2020). The CPS are enhanced with features from the Internet of Things (IoT) technology, providing them with the ability to continuously obtain information from sensors or processes across the factory, and securely forward it to (generally cloud-based) data centers. This massive data production implies the development of new tools based on Big Data techniques, for storing, managing, and processing it. This set of technologies is completed with the Internet of Services (IoS) one, which takes the processed information from Big Data tools and deploys it at the right place and in the right form.

When referred to its adoption in Industry, IoT is known as Industrial Internet of Things (IIoT). Porter and Heppelman (2015), uses the concept of IIoT and describes the way it makes possible to connect devices and obtain data from reading the devices. In the same work is explained that linking combinations of readings to the occurrence of problems can be useful, and even when the root cause of a problem is hard to deduce, those patterns can be acted on. Data from sensors that measure heat and vibration, for example, can predict an impending bearing failure days or weeks in advance. The authors remark that capturing such insights is the domain of big data analytics, which blend mathematics, computer science, and business analysis techniques.

This article begins by proposing the conceptual framework, then it stablish the objectives and hypothesis of the research, and goes to the results of the analysis around the idea of IIoT and AI/ML as a solution to improve industrial processes within the framework of the Industry 4.0 model. Methodologically, a search was carried out through an exercise on Scopus indexed database, and get some findings on commercial solutions like Siemen´s Mindsphere and Canvass Analytics AI/ML solution. The results of the work are thoroughly analyzed to finally present conclusions and emerging future work. Because the quality of energy supplied can adversely affect its operation, oftentimes leading to loss or degradation of equipment, product, revenue, and reputation, plant managers must weigh the advantages of implementing a monitoring program.

The second section of this paper shows three methods for monitoring systems of solar plants. The third section discusses communication and monitoring system for wind turbines, and finally the conclusion is discussed in the fourth section.

II. CONCEPTUAL FRAMEWORK

Searching for the drivers of competitiveness in digital business models, Grover et al. (2018) consider big data as a high impact tool for potentially important economic and social value and for gaining competitive advantage. In this article it is affirmed that big data has grown from a $6.8 billion industry to $32 billion industry only in three years and forecasts the market of big data technology and services to grow at a 23.1 percent compound annual rate, reaching $48.6 billion in 2019. Therefore, with the volumes of organizational data moving past terabytes to tens or even hundreds of petabytes, businesses and information technology (IT) leaders are embracing unique opportunities to capitalize on big data to gain the competitive advantage. It is also considered in this article that companies are spending more than 10 percent of the IT budget on data and are considering big data and analytics as a strategic asset to support their decision-making and improve business processes

Da Silva et al. (2019) observe that opportunities for the development of smart industries have expanded and production processes evolution is driven by the demand for more efficient technologies and procedures, quality standards and cost reduction, and also by technological improvement. Furthermore, a large variety of issues are discussed on Industry 4.0, the main focus of the new production paradigm is to bring into existing industries more intelligent and adaptable processes, with better use of production resources. In the article the authors give an interesting approach to industrial process optimization and smart manufacturing.

An interesting article about the evolution of Artificial intelligence (AI) is brought by Thomas Davenport (2018). In this work he states that analytics 4.0 is the next step in analytical sophistication for organizations, and it is the era of artificial intelligence or cognitive technologies. It became widely adopted – with adoption rates, depending upon geography, of 20 to 30% across large enterprises in 2016 and 2017. It features not only the use of AI methods, but also greater use of autonomy in the execution of the methods, particularly automated machine learning (ML).

A concept that needs to be consider when talking about new business models under Industry 4.0 paradigm is uncertainty. To cope with this fact, sensing and rapid response when planning a new strategy is critical. Walas Mateo (2020) observed the importance of change management when adopting the new practices under the digital paradigm. A tool that could help to develop and find a business or operating mod-el that really works is an agile methodology called Lean Start Up. The real challenge is to develop and validate the value proposition, and look for a model that facilitate optimizing processes, or to consolidate sales and scale the volume of business.

The Lean Start Up methodology created by Eric Ries (2010), collecting the adjective "lean" widely disseminated when describing production methods developed by Toyota and other Japanese manufacturers for dispense with everything that is left over, hinders and lengthens the Productive processes. The fundamental objective of Lean Start up is shortening the product development cycle and employing agile development methods, with validation tests by the market, to match the processes to the acceptance of the clients, adjusting and pivoting -when needed-Indicators are used incremental to measure the result of the actions on the interested customers and sales and the model is analyzed and controlled appropriate growth based on acquisition costs, of customer retention and the value of customers throughout its life cycle. In sum, a set of techniques for match the product development processes with the customer discovery and development.

Iansiti & Lakhani (2020), refers to platforms and their integration that allows an effect of extraordinary scope when talking about digital operating systems, allowing disruptive business and work models. The authors especially mentions Alibaba and Amazon cases. A platform is an environment where an application runs, and based on network connectivity, this definition has been extended to a space where different users can interact with each other or with physical objects. As a result, suppliers, customers, and other partners become part of a networked ecosystem around the CPS.

The integration and scope of the platforms are generated by being connected through APIs. An API, an acronym for Application Programming Interface, is the mechanism that allows devices and platforms to communicate among them. It is something that facilitates, for example, applications using georeferencing to access information from Google Maps.

This phenomenon of liquid marketplace, as it is called by Iansiti & Lakhani (2020) from the possibility that generates Internet and ubiquity, makes possible to reconfigure global value chains, and integrate different platforms to make easier operations management.

III. OBJECTIVE OF THE WORK, HYPOTHESIS OF THE RESEARCH

Having explored some key concepts in the productive environment under Industry 4.0 framework, this work it is aimed to study and analyse the state of the art about business and operating models using IIoT, Artificial Intelligence and Machine Learning in the industrial environment to improve industrial processes.

This paper aims to take in consideration the issues in the above paragraphs, in the framework of the adoption of IIoT and AI/ML solutions. Some topics to explore is how open innovation, Lean startup and platforms, among other methodologies can help with the challenge that means the disruption that is produced in the industrial scenario when adopting data models.

A paper of the Boston Consulting Group, BCG, (2015), states that the model Industry 4.0 allows faster response to customer demands, increase flexibility allowing the adaptability to manufacturing processes, and provides a tremendous amount of tools for quality improvement in the processes, among other advantages. In line with this statement this paper want to explore the role of IIoT and AI/ML to accomplish the benefits that BCG´s paper expect to reach with the novel manufacturing model.

Another observation that is object of this work is what it is said by Muhuri et al. (2019) about studies that have shown that digitization of products and services has become a necessity for a sound industrial ecosystem. However, these requirements and advanced technologies have made the systems more complex and led to many other challenges such as cybersecurity, reliability, integrity, among other issues. These are the major bottlenecks which needs to be overcome for the successful design and deployment of Industry 4.0.

This work aims to approach one of the edges that shows the Industry 4.0 paradigm, and to explore opportunities and challenges that arise from its adoption, trans-forming traditional value chains to facilitate the creation of value and reach new levels of competitiveness.

IV. SOME INTERESTING FINDINGS REGARDING IIOT AND AI AS PROCESS OPTIMIZATION DRIVER

Davenport (2020), writing on the results of a research by Deloitte on the use of AI tools in Industry, highlights how barriers to the adoption of artificial intelligence tools have decreased. Based on a survey of more than 2727 global executives from nine countries, and their organizations have all adopted AI. The key facts that emerge from the article is that the respondents feel that AI is getting easier, and will continue to do so.

Then there are two interesting insights from the article cited in the above para-graph. The first one, is the preference for buying ready-made AI technology over building it. Indeed, at some point it will be difficult not to buy. Another item points that 74% of these executives agreed that “AI will be integrated into all enterprise applications within three years.” In terms of today’s practice, 50% say they will either “buy all” of their AI capabilities. The second, is about the risks the adopter see about AI. Some of the specific risks that most concerned respondents were cybersecurity issues, AI failures that might affect business operations, misuse of personal data, and regulatory changes involving AI/ML.

Walas & Redchuk (2021), refers to the business model of Canvass Analytics, www.canvass.io. The start-up is funded by Gradient Ventures, Google’s AI focused venture fund investing in and connecting early-stage start-ups with re-sources in artificial intelligence. This start-up had developed a business model based on an AI-powered predictive analytics platform for Industrial processes. Its customers include leading manufacturing and energy companies globally. The business model is based on data from IIoT solutions to provide de predictions through machine learning algorithms. It also works in an As a Service model on Microsoft Azure cloud platform.

At the paper cited before, the authors point that the start-up provides a solution that automates the entire data science process, eliminating consulting data science projects. Canvass business model has accelerated the time to insights 12 times faster than other solutions and approaches. The solution is developed specifically for the industrial sector.

Another business model that got the attention of the authors of this paper, is the one provided by Siemens which is called Mindsphere. Sanders & Wood (2020), point that good example of intentionality in the use of AI comes from Siemens, which evolved from an energy equipment firm into a leading provider of electrification, automation, and digitalization solutions with energy-efficient, resource-saving technologies driven by AI and the Internet of Things (IoT) in service. The German IT provider is launching a combination of hardware and software that enables AI throughout its approach called Totally Integrated Automation (TIA) architecture, proposal that aligns Siemens' mission with its AI strategy. MindSphere is a cloud-based IoT operating platform that reaches into industrial user-operated controller and field device products. The

MindSphere's neural processing unit module allows human users to benefit from Siemens' in-house AI capabilities, while also enabling human users to impart their own experience to train the machines. Smarter machinery with TIA architecture leverages AI to advance the company's maturity, while increasing flexibility, quality, efficiency, and cost-effectiveness for its end users.

To complete the work aimed at this paper a bibliographic search on Scopus Data base was made. The search brought some articles with interesting insights to be considered regarding the hypothesis and objectives of the research. The articles were scanned and the results are described below.

The first paper that got attention for this research is the one from Silveira et al. (2020) that studies Industry 4.0 in the semiconductor industry, where high reliability and low operating costs are critical for a business' success. In this context, this article proposes an Industry 4.0 Pilot as a compilation of lessons learned during an end-to-end development of a reference design applied to a semiconductor packaging and test company. It is explored the requirements of clean rooms and information related to sensors and data acquisition boards, in addition to performance details and con-figurations pertaining to visualization tools and warning notifications from AI tools.

Yang et al (2020) observes that smart manufacturing (SM) is a new paradigm that allows manufacturing to enter its fourth revolution by exploiting state-of-the art sensing, communication and computation as the IIoT. Through the use of high-performance computing and advanced modelling, SM aims to improve the flexibility and adaptability of manufacturing. This paper addresses this trend by reviewing the combined use of data-driven and knowledge-enabled hybrid models (HM), and dis-cusses how such techniques seamlessly fit in the SM platform. Furthermore, a discussion of the new paradigms of HM enabled by the SM platform is given, highlighting their importance in future large-scale applications of the SM platform.

The paper from Lara et al. (2020) consider that with the rise of trends such as IIoT and cloud manufacturing, that seek convergence of IT (Information Technologies) tools in OT (Operational Technologies) networks, OT and IT analysis are highly sought after in today's industries striving for real-time analysis of data. To analyze the data in the OT and IT domain it is necessary to use models, which not only focus on describing both domains but can also show the relationship between them. In this paper, it is presented a technique that uses the operational data, produced in an organization from IIoT solutions, in order to model OT, with the purpose of applying analysis methods.

Hansen and Bøgh (2020) in their paper present a comprehensive survey and research of how widespread AI and IoT are among manufacturing SMEs, and discusses the current limitations and opportunities towards enabling predictive analytics. Firstly, an overview of the enablers for AI and IoT is provided along with the four analytics capabilities. Hereafter a comprehensive literature review is conducted and its findings showcased. Finally, emerging topics of research and development, making AI and IoT accessible technologies to SMEs, and the associated future trends and challenges are summarized.

Park et al. (2020) points that Smart Manufacturing Systems can connect raw materials, production systems, logistic companies, and maintenance schedules using the capabilities of industrial IoT. These connections are creating CPPS and linking functions across the entire product lifecycle. These connections are possible today because of the advances in DM technologies that can facilitate factory design, redesign, and analysis in CPPS and help to continuously and efficiently manage factory performance optimization. However, the paper concludes that implementing DM, especially in SMEs, is difficult because the required interface standards and data schema do not exist.

The article from Merkaš et al. (2020) identifies that blockchain's in combination with IoT elements in logistics and transportation, contributes to business process optimization, supply chain traceability and transparency, and significant financial savings. However it can be noticed that there are limitations as blockchain is at a relatively early stage of development with most projects.

Seetharaman et al. (2019) consider that IIoT solutions comprises four key capabilities: connectivity, big data, advanced analytics and application development. IIoT has the potential to provide a high level of synergies between the 4 Ms of manufacturing, namely, man, machine, material and method. Practical implications: It is in the interest of service providers to collaborate and provide a universal solution to retain legacy systems to minimize the investment and reduce the security threat, which could boost IIoT adoption while ensuring that manufacturers are able to lever-age this new technology efficiently.

Vatter et al. (2019) it is affirmed that IoT, big data, data analytics and cloud computing, are changing the production into the next generation of industry. To address these challenges intelligent manufacturing in combination with data analytics plays an important role. In this sense, the integration of prescriptive analytics in manufacturing may help industry to increase productiveness. This paper highlights requirements for a prescriptive analytics based production control, so called prescriptive automation, and finally points out field of activities in this topic.

Finally, Khakifirooz et al (2018) refer to big data analytics as driver for effective manufacturing intelligence for yield management in semiconductor manufacturing that is one of the most complex manufacturing processes, as the authors observes, due to tightly constrained production processes, complex process flows, sophisticated equipment, volatile demands, and complicated product mix. Indeed, the increasing adoption of multimode sensors, intelligent equipment, and robotics have enabled the IoT and big data analytics for semiconductor manufacturing. The study develop a framework based on Bayesian inference and Gibbs sampling to investigate the intricate semiconductor manufacturing data for fault detection to empower intelligent manufacturing. The proposed approach was validated through an empirical study and simulation. The results have shown the practical viability of the proposed approach

V. CONCLUSION

Regarding the empirical evidence, it can be seen that the solutions offered by Canvass Analytics and Siemens seem to have a holistic approach to cover several key issues in order to ease the deployment of IA/ML in Industrial Processes, and create value from data that has been collected by IIoT and is ready to use in an Historian Data Base. Both solutions are somehow aligned to an agile deployment as the one proposed by the Lean Start Up methodology, they both could talk with other plat-forms through APIs making possible the liquidity pointed by Iansity and Lakani (2020).

Both solutions seem to be prepared to take advantage of what Davenport (2020) about the preference for buying ready-made AI technology than developing custom made solutions.

On the other hand, it can be seen that the concept at the moment is well known and mastered by Researchers, Mathematicians, and engineers in software and operating research field, among others.

From the work of Merkaš et al. (2020) and Park it can be concluded that the process optimization is not only in the plant shop floor, but along the supply chain as well.

The works of Khakifirooz et al (2018) and Silveira et. al (2020) seems to confirm the benefits of applying IIoT, IoT and Analytics in complex production environments like the semiconductor industry. And give some answer to the questions rised in the hypothesis about adaptability to manufacturing processes to allow faster response to customer demands, and process improvement.

Regarding the role of the customer and operators in the shop floor, seems people have a central role in new operating and business models. It can be said that each new opportunity will require the participation of people and departments who are today isolated in their silos, and so creating multidisciplinary teams.

Collaboration with other companies will be the norm once it is understood that the world is too complex to be solved in isolation. In this line, the work from Seetharaman et al. (2019) gives some light about the knowledge of the subject considering the manufacturing 4Ms and the potential synergy that the featured solution can provide.

The article from Vatter et al. (2019) pointing the importance of the integration of prescriptive analytics in manufacturing to facilitate increase productivity in industry, and the role of IoT and data analytics is an important validation for the hypothesis raised in this work.

A last point to raise is in line with the work of Lara et. al (2020), regarding integration between IT and OT and the adoption of analytics models. This issue seems to have much more edges to explore and should be treated deeper in future work.

Finally, a key topic to explore in future work, is how process operators or industrial engineers can cope with the challenge that means the disruption that is produced in the industrial scenario when adopting data analytics models. Therefore, the question is the way the shop floor will capture the value that generates the AI/ML, should the process operator or industrial engineer at the process level go further in the master of analytics tools, or the solutions that managers should buy according to Davenport (2020) will be tuned to the language and needs of the people that work in the process.

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