Process Optimization in the Steel Industry using Machine Learning adopting an Artificial Intelligence Low Code Platform

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Abstract.

Traditional industries like steelmaking, are in the spotlight for the need of improving processes towards net zero emissions. This article presents a case on a new business model to ease the adoption of Machine Learning (ML) to optimize industrial processes, applied to a blast furnace at a steel company. The focus of the paper is to illustrate the way a ML platform with a Low Code solution approach can give results in two months to optimize a production process at a steel mill. The methodology used in the case allows obtaining a data model to be validated in less time than conventional approaches. This work pretends to give more light to the use of industrial data and the way traditional industries can evolve towards the industry 4.0 paradigm. The adoption of the low code solution is based on lean startup methodology. The cycle to obtain valid results includes the involvement of people from the process as well as analytics experts. At the end it can be seen that the solution contribute to improve Operational Equipment Effectiveness (OEE) and lower energy consumption. Besides process operators became empowered with the predictions that give the platform.

Keywords: Lean Startup methodology, OEE, AI/ML, Low code platform, Net zero emissions, Industry 4.0.

1. Introduction

This paper aims to go deeper from previous research [1] and addresses the adoption case of a Machine Learning (ML) platform through a new business model [2] in the steel industry to add value in a critical process, and evolve towards a smart manufacturing or Industry 4.0 (I4.0) model. The case pretends to highlight the opportunities that low code Industrial platforms, this time an Artificial Intelligence (AI) solution is featured, can generate to transform traditional factories toward a smarter and more efficient environment, and how people on the shop floor can be empowered by the information these types of solutions produce.

Steel making is a key industry in terms of environmental sustainability in the Net Zero Carbon emissions objective. Going further in the level of criticality that steel industry has reached, [3] points that there is an unprecedented focus on safety, environment impact and sustainability. According to this paper there is a growing concern in maintaining the social license to operate. All those challenges, combined with ever-changing commodity prices and demand paradigm, have accelerated the steel industry's pursuit of sustainable solutions that are capable of helping improve operational performance across the entire value chain.

The previous work [1] highlight the disruptive potential of AI, and ML, to generate new business models and opportunities for startups according to [5]. It is remarked the rise to radical new operating models, this paper pretends to illustrate a case linked to this affirmation, and how it can be applied in the industrial environment.

An issue to consider when talking about I4.0 model is the intense use of data to leverage decision making and facilitate management, according to [6] there is an important quantity of legacy, enterprise, and operational systems data that is not properly used. The article remark that many industries are sitting on a goldmine of unexplored historical, legacy, and operational data from their manufacturing execution systems (MESs) and enterprise resource planning systems (ERPs), among other software sources, and they cannot afford to miss out on its unexplored potential. However, only 20–30% of the value from such available data-at-rest is currently accrued.

Finally this paper approaches lines raised from previous works [7] regarding the implications for people in the process and digitalization, for the success of AI/ML as process optimization driver under I4.0 paradigm. The methodology presented in this work intends to ease the the adoption of the new model through a co creation process between experts from the industrial process, and software engineers from the AI platform.

2. Methodology. A Lean startup approach proposed by an AI Low code Platform

The methodology to be applied in the case considers the opportunities to adopt AI/ML in the steel industry. The approach is based on Low-Code solution [8], and Lean Startup methodology [9] to achieve results in less time than conventional adoption processes of analytics solutions, making possible to democratize artificial intelligence and machine learning in traditional industrial environments.

The value proposal of the new business model presented by the Low Code Platform (LCP) focuses on shortening the adoption cycle of AI/ML in industrial environments by using prebuilt templates for manufacturing processes.

[10] Affirms that LCPs facilitate achieving objectives at the core of business information systems research such as increasing productivity and reducing costs of developing and maintaining enterprise software systems and improving organizations' ability to adapt software systems to rapidly changing requirements, and empowering users. The author also points that it is not at all clear what distinguishes LCPs from existing

software development facilities, such as classical integrated development environments (IDEs)and tools for model-driven development (MDD).

The LCP used in the case of this paper, offers seven templates: Forecasting, Anomaly Detection, Optimization, Simulation, Failure Prediction, and Defective Part Prediction. The template to use in each case depends on the nature of the process and the opportunity to address.

These preconfigured frameworks allow users in the shop floor to understand easily what I aimed with the data model, have it earlier and evaluate results faster. The adoption cycle begins working with the model offline, in a co creation space between process and software sides. Once created the analytic model is fed by data from the historian database. This way, the operators evaluate results and gain confidence by iterating through multiple experiments.

Finally, the model is deployed into operations, when is fed with real-time data from the industrial processes. The solution is offered in as a service (SaaS) model, ingesting data in a data series format from MES; or Industrial Internet of Things (IIoT) platforms. This way the AI/ML software is integrated in the industrial operation with the shop floor solution, and work with data in real time to generate the predictions to the process operators. A complex issue for the industrial environment, and a weakness reported by the study presented by [11] is cybersecurity. This issue is tackled by hosting the platform at Azure Microsoft Cloud (https://azure.microsoft.com/). This cloud solution also provides infrastructure needed for the requirement of AI/ML models.

To validate the effectiveness of the platform and have results in a shorter period than traditional approaches, a Lean Startup methodology is used. This way non-value adding activities are minimized and people from the industrial process can be involved earlier, while introducing the new solution. The Lean Startup methodology has three key principles: to replace planning with experimentation, the ‘getting out of the building’ approach and lastly, agile development [12].

The experimentation process is described by the Build-Measure-Learn feedback loop consisting of three steps: build, measure, and learn. In the first step, build, it is essential to create a Minimum Viable Product (MVP) using as less resources as possible after identifying the most important hypotheses [9]. The goal of building an MVP is to identify the proposed solution’s potential [13] and the value for the customer. The measure step aims at collecting data that can verify or dismiss the hypothesis made about the solution to be offered [9]. In the learn step, the goal is to know about the hypotheses from collected data. The learning process shows if an underlying hypothesis can be verified indicating that the MVP matches a customer requirement.

3. Adoption Case in the Steel Industry

The case examined was the process in the blast furnace of a North American steel company, where there was a need to optimize the production line by improving the quality and quantity of performance of the BF. As mentioned before, these are complex and dynamic processes that generate hundreds of data types with high variability. This leads to management challenges to maintain consistency of production quality, lower energy consumption, and use less silicon.

It should be considered that inconsistencies in quality in the foundry process generate excess scrap, rework, and production delays, among other issues. Traditional quality control was done through samples that were analysed in a laboratory. The problem with this methodology is that if there was an inconsistency, the problem was solved in a reactive way, when it had already occurred.

On the other hand, it must be considered that the process ran in three eight-hour shifts, and the operators were different, each with their own criteria for and experience in the process. Then, its control varied depending on each person. In addition, the smelting process included a large number of chemical and thermodynamic variables that were very difficult to monitor and control.

The firm generated real time data from the production processes through a MES software, OSI PI from OSIsoft [14]. This data is stored in historian-type databases.

4.1 Adoption process and Results

To address the improvements in the process, the steel company chose the solution proposed by the AI platform with the following objectives:

1. Identify the parameters that influence the maximization of production performance using process data generated by the OSI PI platform.
2. Predict product quality and performance at different intervals, and use those predictions to adjust control parameters in real time, thus maximizing product quality and performance.
3. Apply a proactive policy for the resolution of problems and anomalies of the process based on having advance information about what happens in the casting process.
4. Institutionalize the best practices of the operators and provide those responsible for the information processes that facilitate decision making.

The case was developed using the Build-Measure-Learn feedback loop detailed previously in section 3 and displayed in figure 1 at the bottom of this section. The first phase of the methodology, BUILD, started after defining the adoption scope and its objectives. The process experts at the steel works self-trained with the support of experts in data analysis at the Startup. Meanwhile, both parties collaborated with to clarify doubts and specific topics that arises at the data experts' side, about metallurgy issues and characteristic of the process at the BF.

An issue to highlight that make possible the adoption of the LCP, is that there was enough data available generated by the MES solution, it only needed to be normalized. Then the process engineers from the steel works began working with the analytics and math experts to analyze and understand the methodology and technical details of the milling process. The first step of the methodology took three weeks.

An observation that should be done is that there is no existing baseline for this use case, the operator could not predict such behavior by the traditional operation. It only can be estimated based on a quick metallurgical balance. In this case, the operation depend on the intuition of the operator and even on management policies.

The following stage according to the Lean Startup methodology was the MEASURE one. In this phase a model was produced in the software platform and the plant users evaluated the use case with historical data ingested on the platform.

A data exploration and evaluation of data model by the BF Process Managers was performed and analytics experts from the software startup provided support at all times. The process engineers went thought the model, and finally they validated it.

The second phase of the methodology was completed with the model going live at the platform on line. Real time data from the MES solution started to be ingested to the cloud based solution. The integration was made by software specialists from the Startup. Besides the software solution has an Aplication Process Interface (API) that simplifies the integration with OSI PI platform. This way the process users accessed to the ML solution with continuous support from the provider. This cycle took six weeks.

The last stage was the one called LEARN, according to Lean Startup methodology. In this last phase the plant staff recognized the value that the use case contributed. Results were analyzed by the software supplier and plant engineers. The use case was reviewed on a platform mapping session where both teams gained deeper insights into data, business value, and complexity of previously identified use cases.

The adoption process took two months until project kick-off in order to have the model on line ingested with real-time data, and generate predictions to suggest better operation conditions to the furnace operators. In this period, the people in the process were taught how to use and understand the information given by the solution, while people from the platform provider adjusted the model. The validation was done together by the software engineers and plant operators.

The platform made it easy to define the relationships between variables that significantly affected the production result, such as quantity of silicon added and fuel consumption. The AI models collaborated to determine which of the control variables had a positive or negative impact on production quality. By applying ML-reinforced learning through the forecasting template.

As a result of predictions generated by the ML LCP, the steel firm obtained a competitive advantage by improving OEE, and achieving consistency in quality with silicon content always at a normal range. Additionally, by defining set points in real time for fuel consumption, energy savings were facilitated. The OEE improvement was achieved mostly by reducing the percentage of scrap, thus reducing costs and producing higher quality steel. There was a triple optimization for the firm: reducing costs, improving customer services revenue. Moreover by improving energy consumption the firm is aligned with Net Zero Carbon emissions objective.

The use of ML methods employed alongside domain knowledge of BF specialists facilitated a greater knowledge to process people that was augmented continuously. This allow to work on continuous improvement and optimize Key Performance Indicators (KPIs), evolving toward more mature management systems.

4. Conclusions

The case addressed the adoption of a new business model based on AI/ML in a traditional industrial environment and on the complex steel smelting process in a blast furnace. The solution came from a startup, and had an advantage over new methodologies that shortened times and simplified adoption of analytics in the industry. The distinguishing feature of the approach with respect to other works was the Low-Code approach, which eased the use of AI/ML by process operators with little math or statistics knowledge, and shortened adoption times radically.

In line with the above paragraph, change management was simplified toward an agile approach; the new business model generated results faster and with lower complexity than traditional analytics solutions. This was because the model proposed by the platform of the case, is centred on the end user, the process operator. The Low-Code model from the startup eased time-consuming and risky tasks linked with software development and algorithms. In this way, the business model proposed in this paper helped to democratize AI/ML in traditional industries, making the adoption of these types of tools easier for a broad segment of people.

The improved process was based on predictive analytics aimed at exploiting the huge treasure of legacy operational data and overcoming some challenges of real-time data analytics. The potential of the proposed approach is high in traditional industries that have not benefited from the advancements of Industry 4.0, and in most cases have just started investigating the potential of data analytics and machine learning for the optimization of their production processes.

On the other hand, the need for a large amount of operational data is an important limitation for various traditional industries that are still lagging on digitalization. This issue is an important weakness of industries that could use data models to improve the remaining useful life (RUL) of heavy equipment, reduce carbon footprints, and reduce non-value-adding activities, among other wasted opportunities.

Another point to highlight is the opportunities that the smart manufacturing paradigm opens to startups and their innovative business models that offer solutions to ease the adoption of AI/ML in the industry. This case showed how a business model using AI/ML focused on a No-Code/Low-Code strategy could shorten implementation cycles from several months to a couple of months, as shown in the case at the steel firm.

Using information captured from the process that is generated by shop floor integrated platforms such as MES or IIoT, seems to be a key point to improve processes, and evolve towards AI/ML models. Not doing so should be considered a waste that translate into lack of competitiveness for industrial firms.

Finally it could be seen that I4.0 model ease data into knowledge to empower people at the industrial shop floor. From the technological side, the case show how OT and IT is integrated from sensors at the plant, MES platform, LCP, and cloud infrastructure to provide knowledge to improve the productive process.

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