Journal of Mechatronics and Robotics

Original Research Paper

Smart Manufacturing in Mining. Adopting Machine Learning to Improve a Copper Milling Process

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Article history
Received: 28-02-2023
Revised: 25-03-2023
Accepted: 28-03-2023

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Abstract: Nowadays industries like mining are focused in the need of improving processes towards net zero emissions and accomplishing with united nations' sustainable development goals. This article presents a case at a copper mine where an artificial intelligence solution is adopted to optimize industrial processes. The paper illustrates the way a software solution using a low code platform framework can democratize the use of advanced analytical tools in the industrial sector to improve production processes. The low code approach is complemented by lean startup methodology to adapt the solution to the industrial domain and establish a co-creation environment among software engineers and industrial processes experts. This study pretends to highlight the use of industrial data and the way traditional industries are migrating towards the industry 5.0 paradigm, empowering people at the plant and achieving more environmentally friendly processes by the use of digital solutions.

Keywords: Lean Startup Methodology, Smart Production, Low Code Solution, UN SDG, Industry 5.0

Introduction

This study goes further from previous work (Mateo and Redchuk, 2021) and focuses on o case of a Machine Learning (ML) solution adoption in a copper mine. The article aims to address the opportunities that low-code industrial Artificial Intelligence (AI) platforms can produce to ease the evolution of traditional production systems toward a smarter environment and how people in the operation process can be empowered by using these kinds of tools.

Nowadays mining needs to maximize the production of minerals like copper and lithium due to the demand for renewable energies. Going further in the level of criticality that mining has reached. Agarwal (2020) observes the importance that safety, environmental impact, and sustainability have achieved recently. This article points out that there is a growing concern about maintaining the social license to operate. All these changes have accelerated the mining industry's search for sustainable solutions to improve operational performance. Besides the author remarks that the proliferation of advanced data analytics technologies, such as artificial intelligence, has opened the door for digital solutions to help industrial companies create value from disparate data sources including sensors, personnel, and operational data.

Endl *et al*. (2021), address the United Nations (UN) Sustainable Development Goals (SDGs), in particular the items referring to industrial innovation, responsible consumption and production, and climate issues. The article from He (2020), on green mining presents an integrated approach considering technology, quality, and environment to tackle the sustainability of mining processes.

The work from Pfau and Rimpp (2021) highlights the potential of AI and Machine Learning (ML), to create new business models and opportunities for entrepreneurs. The authors present conceptual development and success cases. They highlight that the innovative potential of the new business models can generate a new kind of singular startup. Continuing in this line, the article from Redchuk and Walas Mateo (2022) addresses the benefits that new business and operating models on AI/ML can produce to optimize the production environment.

Lepenioti *et al*. (2020) observe that exist an enormous quantity of data from enterprise software solutions is not used. The authors observe that industrial firms have an immense opportunity to use data from their existing digital platforms.

Industrial firms can evolve towards the model industry 4.0 (I4.0) through a novel methodology that considers the use of data models, agile change management, and a Low Code Platform (LCP). To illustrate this idea, the article develops the main concepts and a success case in a mining company.

The author's approaches lines left raised from previous works from Walas and Redchuk (2021), regarding the role of people in the process and digitalization, under the I 4.0 paradigm.

The methodology presented in this study intends to ease the adoption process of the AI/ML solution under a collaborative process between professionals from the industry and software engineers from the LCP.

In the beginning, the article presents a brief study through the Scopus platform. This first part of the work develops concepts about the use of operational data to improve processes in the mining industry and a review of the state of the art in the use of AI/ML in this sector. The key issues of the process to be improved are described and finally, the case at the copper Semi Autogenous Grinding (SAG) mill is presented and at the end results achieved are presented.

AI/ML in Mining, Some Preliminary Findings

This section presents the state of the art in the use of AI/ML in the extractive industry. The works cited in the following paragraphs contribute to establishing a preliminary conceptual framework for the case to be studied.

The paper from Avalos *et al.* (2020), presents the adoption of ML in mining operations to optimize energy demand in a mill at a mine in Chile. The work proposes a methodology using real-time operational variables to forecast the upcoming energy consumption through ML. The article presents a number of predictive techniques and a methodology to cope with datasets from operations and a method to get optimum models.

Flores and Leiva (2021) address the use of AI techniques in order to optimize the industrialization of copper. The article develops a case in a mining operation, where they compared different models for predicting the recovery of copper by leaching using four data sets from the process. The paper describes the whole process from dataset preparation to finally obtaining results, which gave highly competitive values when compared with those obtained in similar studies using other approaches in the context.

The work from Barnewold and Lottermoser (2020) highlights constraints for mining firms to establish which digital technologies are the most effective objectives and requirements of mining firms. The article identifies 107 different digital technologies considered in mining. The article observes that large-scale mining companies acquire and use digital technologies suitable to their needs, whereas small firms do not implement the available digital technologies to the same extent. Smaller operators may require other digital solutions customized to their scale and the needs of such operations.

The paper by Zelinska (2020), observes the potential of ML in mining through its several methods. The article addresses the possible impact to improve processes at the mining firm and maximize the use of equipment. The article highlights the high dependence on information technology, mathematical analysis, and statistics specialists. The article also highlights that ML solutions enable mining efficiency and ensure environmental security.

Ali and Frimpong (2020), observe that the mining sector has been lagging in applying innovative methodologies to improve operations with intelligence. However, the authors present a study that reviews and analyze all the recent automation related work in the mining industry, pointing out the efforts being done to change the trend of innovation in mining. The work provides recommendations to implement Deep Learning (DL), ML, and AI in the mining sector. The article concludes that the mentioned technology could contribute to establishing the extractive industry of the future, providing efficient, effective, and safer machines with sustainable mining operations.

The work from Visser (2020) addresses the growing availability of information and data analysis solutions. The article highlights the need for the involvement and motivation of operations people in the data-driven solution and their empowerment to have a central role in decision-making.

The last featured article to contribute to the conceptual framework is the one from (Sharma *et al*., 2021). In this article the authors highlight the slowness of the mining industry adopting digitization compared to other industry segments. Firms in the extractive sector need to focus on reducing operating costs due to demand fluctuations and rising operating costs. A critical cost is equipment maintenance, which represents between 10 and 30% of direct mining operations costs due to varying operating conditions. The authors present an ML model that optimizes maintenance schedules focusing on data-driven actions to improve Key Performance Indicators (KPI), Overall Equipment Effectiveness (OEE), Overall Throughput Effectiveness (OTE), and Impact Factor (IF). IF upturn is demonstrated through a case study of mining shovels. The IF improvement is also in line with the productivity optimization of equipment according to UN SDGs.

Materials and Methods

The proposed strategy considers the opportunities and limitations to adopt AI/ML in the mining sector as seen in the previous section. The proposed approach is based on a no-code/low-code digital solution (Cabot, 2020) and agile project management applying lean startup (Ries, 2011; Blank, 2018) as a means to accelerate the adoption processes of data-driven solutions and looking for the democratization of AI/ML in traditional industrial environments. In the end, it is expected that industrial users of the solution could interpret process behavior and solve challenges through AI with confidence.

The digital solution that is used in the case is an LCP that looks for easing the adoption of ML in industrial environments and achieve results in less time than traditional approaches. Among the innovative features to facilitate the adoption and use in the industry, the software tool includes prebuilt models. This feature includes templates to approach different kinds of processes and opportunities to address.

The objective of the prebuilt frameworks is to make people in the industrial process understand easily what is aimed with the data model, experiment with the model, and understand and evaluate results faster. The adoption process starts by selecting the most appropriate use case, identifying success criteria, and determining the users to be involved. At this stage of AI deployment assessing data readiness is critical. From this early moment, a collaborative space is created between the process and software sides.

The next step is data visualization and contextualization using the LCP to make the data discovery process easier and faster. Trends or anomalies are identified.

Then AI models are created using pre-built applications that make it possible for industrial engineers to build models without requiring coding skills. This helps reduce the time required for the model training and evaluation process, allowing engineers to test different scenarios and run multiple experiments.

After running multiple experiments and evaluating the model's performance, the models are ready to deploy. An end-to-end AI platform makes it possible to seamlessly deploy models to live environments, where functions across the organization can use the real-time predictions generated. Finally, the LCP could be ready to successfully operationalize, monitor and manage the first model in the operations environment.

The model is deployed into operations and is fed with real-time data from the industrial operation. The Solution is offered in a Service (SaaS) model, ingesting data in a data series format from Manufacturing Execution System (MES); or Industrial Internet of Things (IIoT) platforms. The software solution is placed at microsoft AWC (2022). This cloud solution provides a framework to achieve the calculation power for the requirement of AI/ML models and as a value-added service, the infrastructure includes tools to safeguard data from cyber-attacks.

The adoption strategy of the software solution is complemented with an agile methodology approach to establish a co-creation space between the software engineers that are providing the technical solution, the LCP, and the users who are industry professionals. The agile strategy chosen is a lean startup. This election is justified in achieving the earliest involvement and compromise of the industrial user in the innovation process and the fact that this methodology provides a reasonable framework to deal with uncertainties and reduce non-value activities (Ries, 2011).

The agile adoption process is carried out using a build-measure-learn cycle. The first instance, build, is focused on creating a Minimum Viable Product (MVP) generated by using as less resources as possible. This item is created after defining the most important features the novel product or service is going to offer (Ries, 2011). The objective of having an MVP is to identify the proposed solution's potential and if there is value for the customer (Kerr *et al*., 2014).

The next stage of the cycle, called measure, aims at gathering data from the user to validate, adjust or dismiss the hypothesis made at the previous instance of the adoption process. In the last step of the lean startup cycle, the focus is to give value to the validated knowledge which has been generated till this moment of the implementation cycle. The learning stage proves if an underlying hypothesis can be verified or not and indicates if the MVP is a viable solution to address the improvement opportunity.

To add some more elements to the introduction of the adoption strategy, Scheuenstuhl *et al*. (2021) introduce a case where a lean startup strategy is used to facilitate innovation in established firms. The paper highlights some key issues that favor its use. First of all, the text points to the optimization of resources and the achievement of goals in less time than traditional approaches, another aspect to highlight is the achievement of greater feedback from people involved in the process object of the innovation.

Considerations of the Milling Process to be Improved

The case examined was developed in a copper mine in South American Andes, where there was interest to improve the OEE. Then it was decided to explore the usefulness of the methodology at the Semi Autogenous (SAG) mill. Introducing the solution on AI/ML is aimed to maximize the processed tonnage, keeping the grinding P80 stable (Chelgani *et al*., 2021). While maximizing recovery.

The continuous process to be improved consists of stages of size reduction, the concentration of copper content, and the reduction of water content. The whole process includes the following activities:

- Primary crushing: Reduce the size of rocks to less than 8 using ball mills
- Transport and recovery: Conveyor belts (6 km), gross stockpile (capacity up to 55,000 tons), and feeders that dose the ore to the grinding
- Grinding: Reduces the size of the ore, according to P80 to 240 um
- Pebbles crushing: Stage to help the SAG mill process the ore at the critical size. The product re-enters the SAG
- Flotation: Copper-rich particles are trapped and splittered, getting a copper-rich pulp, the concentrate
- Grinding: Size reduction of the copper particles continues. Step to release the copper
- Concentrate thickening: The first stage of reduction of water content, to a density greater than 1,6
- Concentrate filtering: Continued reduction of water content, humidity less than 8%

DOI: 10.3844/jmrsp.2023.42.47

The main inputs of the process are the characteristics of the ore (granulometry, type, hardness, elements present, etc.,) and the feeding rate. The outputs are the characteristics of the concentrate (moisture percentage, copper content, granulometry, and others).

The feed to the SAG can be increased as long as there is free capacity. Some associated data is that the SAG weight is not very high, pebbles production is less than 800 tons/h, ball mills with available power, and P80 is less than 240 um, as first sight parameters to improve.

In this process, the parameters that can be adjusted are SAG feed volume, of pebbles returned to the SAG, percentage of solids at SAG (relation of mineral vs. water at SAG), and SAG speed, among others.

The industrial process is described in Fig. 1. The industrial process at the plant includes the following steps.

In this process, the possible parameters to adjust were the following: SAG feed volume, Pebbles volume returned to the SAG, Percentage of solids in the SAG (mineral vs. water ratio in the SAG), and SAG speed, among others. Figure 1 shows a schematic of the mill and the process, together with the variables involved. Presented the process at the mine, it should be observed that although there is an expert system that controls the SAG mill, most parameters are set by the operator. The automated system can manipulate SAG feed, SAG speed, and SAG percent solids, but it operates 70% of the time.

A last important observation is that operational processes generate real-time through an MES software, OSI-PI from (OSIsoft Website, 2022). This platform has generated enough valuable data from industrial processes to be used in the AI/ML solution.

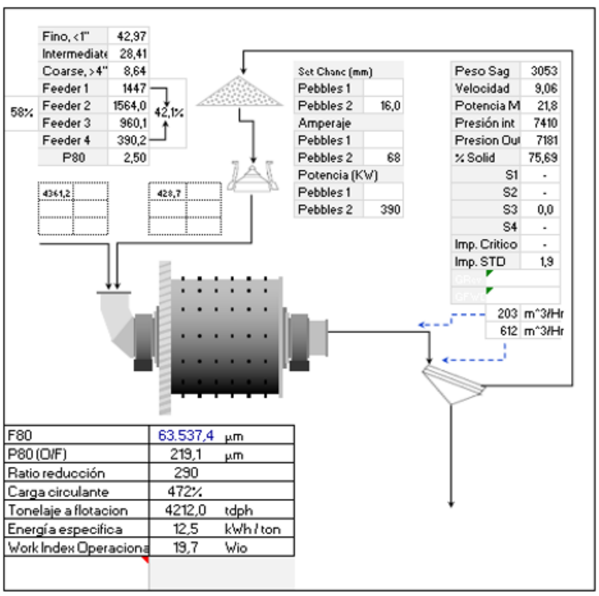

Fig. 1: Diagram of the process at the SAG mill with relevant indicators. Source: Authors

Development of the Case and Results

The adoption of the digital solution to introduce the use of AI/ML in the industrial process of the mine was done using the methodology detailed previously. The process experts at the mine auto-trained with the support of professionals in data analysis from the software Startup. Meanwhile, the process experts from the mine cooperate with the analytics professionals to understand the industrial process and specific topics about metallurgy and particular features of processes of the copper mine.

A point to highlight is the fact that there was enough data from operations available that had been produced by the MES platform. Then this data was prepared for extracting insights. Advanced visualization and contextualization tools from the LCP were used to make the data discovery process easier and faster. Value began to be extracted from historical data taking a deeper dive to identify trends or anomalies and apply these insights to establish the scope and goals of the case study.

It was decided to improve the process at the SAG Mill, then a forecasting prebuilt model from the LCP was chosen to proceed. It was aimed to forecast tonnage-treated specific energy, P80, and recovery. It was expected to have twelve hours in advance notice. The first milestone of the project under the chosen strategy took about 20 days.

At this point is important to highlight that the initial situation of the use case was that the operator only could estimate the parameters based on a metallurgical balance. The success of the operation then depended on the operator and even on management decisions.

Then the data model was produced in the software platform to be used as MVP. The data model was generated using pre-built AI applications by industrial engineers' coding skills.

The following stage of the methodology consisted of experimenting and evaluating the data model in a collaborative environment among mine process managers and analytics experts from the software startup. During the model training and evaluation process, the team went through different scenarios and run multiple experiments. Finally, the forecasting model was validated by process engineers.

This second step of the methodology was completed with the deployment of the model and fed with real-time data from the process of the integration made by software specialists. The software solution has an Application Process Interface (API), that simplifies the integration with the MES solution. This part of the adoption process took nearly 30 days.

In the final segment of the adoption process users began to use real-time predictions to take action over the operation. The information from the LCP was evaluated by both software and industrial engineers. Then the process was changed to work with predictions.

To complete the adoption of the AI/ML solution, all the staff of the process team was trained, the platform was adopted and the process was changed to follow the notifications of the platform regarding the performance of the SAG Mill. The third phase took about 15 days.

Preliminary results show an optimization in energy use and better recovery performance.

Discussion

The studied case addresses a key issue for the evolution of traditional industries into the I4.0 paradigm, the need to speed up and ease the adoption of digital solutions in traditional industrial environments.

The implementation of a solution based on AI/ML in a milling process at a copper mine using an LCP and agile project management proved to improve the industrial process, the adoption process consumed less time and resources, and most important get industry people involved from the beginning in the adoption process.

The solution came from a software startup that leveraged new methodologies that reduce time and simplify the adoption of data-driven solutions in the industry. The distinguishing features of the approach compared to other works are a no code/low code approach that facilitates the use of AI/ML by process operators with little mathematical or statistical knowledge and radically reduces the time adoption.

Aligned with the above paragraph, change management is simplified towards an agile approach, the digital platform generates results faster and with lower complexity than traditional analytics solutions. Something to observe from the case is that the adopted digital solution focused on the process operator. The model proposed by the LCP eases consuming and risky tasks linked with software development and algorithms. This way model proposed in this study helps democratize AI/ML in traditional industries, making the adoption of this kind of tool easier for a broad segment of people in industrial processes.

A key point is that the new solution on AI/ML facilitates augmenting industrial operators' knowledge and easing the process environment with the knowledge provided by the platform.

Another point to highlight is meant by 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. The experience developed in this study makes visible how a business model on AI/ML focused on no code/low code strategy could shorten implementation cycles from several months to a couple of months as shown in the case at the copper mine.

The process improvement is based on predictive analytics which relays on exploiting the huge treasure of legacy operational data and overcoming some of the challenges of real-time data analytics. The potential of the proposed approach is high in traditional industries that have not benefited from the advances of I4.0. In most cases, they have just begun to investigate the potential of data analysis and machine learning for the optimization of their production processes.

On the other hand, the need for a large amount of operational data is a major limitation for several traditional industries that are still lagging behind in digitization. This problem is a major weakness for industries that could use data models to optimize energy demand, reduce their carbon footprint and reduce non-value-added activities, among other missed opportunities.

A final observation deserved the use of the methodology that demonstrates how the adoption of the LCP through an agile methodology has an impact in shortening the adoption times and in facilitating the co-creation of the model between the professional expert in the industry and the software expert.

Acknowledgment

The authors wish to thank to the program Lomas CyT, UNLZ, Argentina for the support for the research that make possible this study.

Funding Information

The authors wish to thank the program “Lomas C y T” from Universidad Nacional de Lomas de Zamora (UNLZ) for funding the project that generated this study.

Author’s Contributions

Federico Walas Mateo: Conceptualization, methodology, formal analysis, investigation, and written reviewed and edited.

Andrés Redchuk: Resources, visualization, supervision, project administration.

Julian Eloy Tornillo: Written reviewed and edited.

Ethics

The authors declare no ethical issues that may arise after the publication of this manuscript.

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