An Explainable AI Approach for Predictive Bath Temperature Regulation

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Abstract

Consistent bath temperature regulation in aluminium smelting pots remains challenging despite technological advancements. In potlines, bath temperature plays a crucial role as it has a direct impact on the productivity of the pots. In the past, a few Artificial intelligence/Machine learning (AI/ML) models have been developed that offer predictive capabilities, but these models lack practical interpretability for control actions. This paper introduces a novel approach using SHapley Additive exPlanations (SHAP), an explainable AI framework, where this AI model not only does the prediction but also uses the same data to prescribe actions. This method, not only predicts temperature variations but also uncovers factors causing these fluctuations, filling the gap between continuous thermal measurements for real-time monitoring and control. It autonomously generates actionable insights 16 hours before measurement, enabling potroom engineers to implement effective control strategies. This has resulted in decreasing the number of pots with temperatures greater than 970 °C per day.

Keywords: Bath temperature, Temperature regulation; SHapley Additive exPlanations (SHAP).

1. Introduction

Primary aluminium is produced in Aditya Potline, located in Odisha, India, which operates at about 960 °C. The pot design and its operating parameter play a crucial role in pot thermal balance, which is reflected in bath temperature and superheat. Controlling bath temperature on day-to-day basis is tedious task. Multiple parameter variations like AlF_3, alumina enrichment, high energy anode effect, pot high voltage, add multi-dimension complexity to the whole process of controlling temperature. Both, high and low temperatures are equally problematic as both contribute to productivity loss, and pot life reduction. Higher temperature tends to melt ledge, thereby disturbing bath chemistry and metal purity. Lower temperature on the other hand tends to increase overall instability of the pot, thereby impacting production. To address such complexity, Digital Twin of aluminium smelting process plays an important role [1]. The proposed solution in this paper has three functionalities: first, it predicts whether the pot will be on higher temperature, second, why it will be on higher side, and third, actions needed to prevent it.

In the approach discussed in this paper, machine learning and SHAP (SHapley Additive exPlanations) is preferred over other the high-fidelity models, due to numerous reasons starting with interpretability, which lacks in other high-fidelity models [2]. Other reasons include shorter execution/running time of the model, facilitating scalability, flexibility and automation.

Machine Learning (ML), a crucial subset of artificial intelligence, is fundamentally reshaping our world. Despite its transformative potential, ML models are often criticized for their lack of interpretability, as most of details are hidden in a 'black box' model. SHAP is a tool that seeks to address this issue by providing insights into the decision-making process of ML models. SHAP in the past has been used in multiple domains including Manufacturing, Healthcare, Finance and Marketing. In manufacturing SHAP has aided plant engineers to interpret machine learning models to identify causes of machine failure and increased uptime. In finance, it has been used for credit risk assessment of financial institutions.

Primarily, without SHAP, understanding the reasoning behind ML model predictions become challenging. This opacity can lead to mistrust among users and stakeholders, making it difficult for them to rely on the models' decisions and to take control actions. In case of bath temperature prediction, there were similar challenges in the beginning. We were having prediction about pots which will be at higher temperature but due to lack of interpretability, Operation/ Process team had to spent lot of time analysing data of the predicted pots and identify control actions. Hence in this study the focus had been to provide the key controllable parameters, which would help in regulating the bath temperature in desired range for individual pots. In specific, this paper underscores the importance of interpretability tools like SHAP in effectively deploying ML models and how this technology helped in effectively improving bath temperature regulation in our potline.

2. Explainable AI in Potroom

Explainable AI is a set of methods and processes that helps humans to retrace how AI algorithm reached the result. In simpler terms, it helps humans to understand why AI has given certain predictions. In our case we have utilised this technology to identify reasons behind bath temperature increase. Explainable AI has lot of potential in potlines. It can be used in hot metal production improvement, and high availability of equipment. For example, it can be used for current efficiency pattern analysis, variations in bath chemistry, equipment downtime analysis, etc.

In Figure 1, we summarize our machine learning approach in four phases: First phase is training and development, where model is trained on labelled historical data. Second phase is for testing and deployment, where model is tested on unseen data and deployed after achieving user required accuracy, in our case it was 70 %. The model is then deployed. Third phase is interpretability, where model predictions are used in real time for taking control actions based on interpretation by SHAP. Fourth phase is for monitoring, where a mechanism is placed to check variations in data; if variations are different from the training data set, then the model is retrained. All the phases will be explained in detail in this paper, along with diagrams.

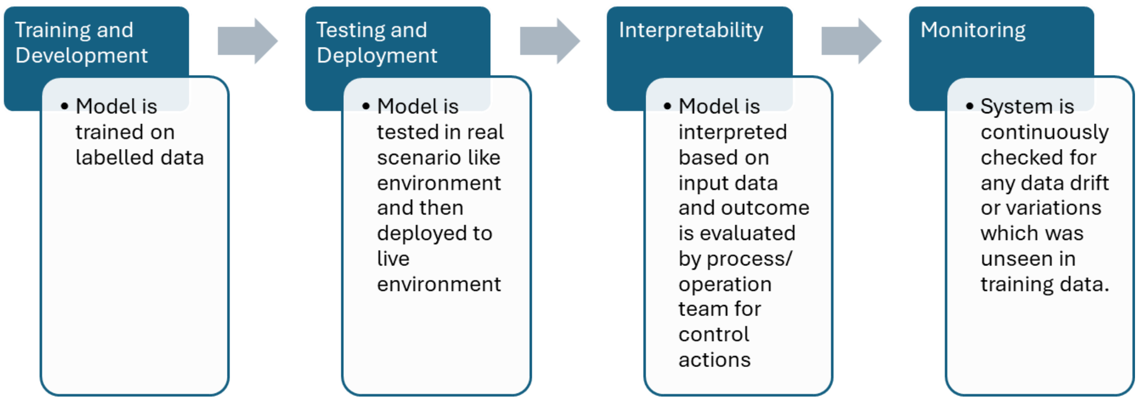

Figure 1. Phases of the model.

and testing, feedback received from process and operation team, it was concluded that just by providing the pot name did not work, as after prediction, the team had to spend a lot of time to do manual analysis to identify and take control action. After doing lots of testing, it was found that the SHAP will be the right solution for the problem, and it eventually solved the problem. After getting features responsible for the prediction, a loo- up table was created to do prescription based on output received after interpretation.

Although in this study focus was on just the bath temperature prediction, it becomes evident that SHAP holds immense potential for enhancing transparency, trustworthiness, and interpretability in predictive modelling of other key parameters. With further research and refinement, this technology has potential to pave the way for more interpretable and actionable insights in the potline in the future.

5. References

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