Artificial Neural Networks for Predicting and Improving HF Generation and Recovery Efficiency

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Abstract

Brownfield aluminum plants have increasingly focused on controlling hydrogen fluoride (HF) emissions due to amperage increase, which can lead to higher gas temperature and HF generation. Increase in HF emissions can restrict strategic initiatives such as amperage increase unless smelters generate significant investment to boost the gas treatment center (GTC) capacity. Previous research has focused on the hooding and scrubbing efficiencies to reduce HF emissions. Other more recent investigations have produced models to estimate the HF generation following feeding periods, and depending on the relative air humidity, as well as the loss on ignition (LOI) (volatile hydrous) in alumina. However, none of these models yields concrete operational applications for decision makers in allowing the quantification of HF emissions during each of the main operational activities. Thus, the models do not incorporate structural, systemic, or operational factors into the quantification of individual sources of hydrogen fluoride emissions. In a modern Rio Tinto smelter, supervised machine learning (SML), comprising artificial neural networks (ANN), was used to analyze the factors and the distribution of HF emissions in a multifactorial modeling problem. The model uses a multi-dimensional dataset and can predict, with over 90 % accuracy, the influence of systemic, structural, and operational factors on HF emissions. These factors can hinder amperage increase. The results showed that the most effective way to improve HF recovery is to scale down generation by operational strategies and process parameter settings. This research contributes to business practices by providing a statistical capability for predicting and planning HF emissions according to draft/kA ratio, seasonality, process settings, systemic factors (work delays), operational excellence, and structural factors (e.g., anode geometry, gas kinetics, temperature, etc.).

Key words: Gas kinetics, HF generation and emissions, HF emissions planning, Artificial neural networks, Statistical modeling.

1. Introduction

Primary aluminum smelting can generate significant HF emissions. One of the most important responsibilities of the aluminum manufacturers is to protect worker safety, ambient air, water, and soil. Companies must measure HF concentrations in smelters at multiple locations through gas treatment center (GTC) stack sampling or continuous emission monitoring (CEM) at roof vents. The gas treatment centers then play a crucial role in cutting down HF emissions through internal recycling via adsorption on smelter grade alumina. Production-rate increase requires brown field smelters to improve their processing capacity, including GTC capacity, standard work methods, and process control. Adding more stress to resources operating at full capacity can have harmful effects. According to research, GTC gas recovery performance can suffer if gas temperature rises due to increased potline amperage and internal heat [1]. CEM device alone cannot prevent HF emissions generation, even though it can detect abnormalities. Smelters need a more compelling and proactive approach in providing robustness against high HF generation.

In most countries, governments are actively protecting workers safety and environmental receptors through legislation [2]. Plants operating aluminum smelters need to meet hydrogen fluoride emission limits imposed by authorities. Not meeting these requirements could expose the plant to fines or even to reduce or halt the production. Rio Tinto is a responsible company that follows ecological standards to reduce emissions and protect the environment and was the first company to obtain certification by Aluminium Stewardship Initiative (https://aluminium-stewardship.org/). Their modern plants go beyond regulatory requirements. The mean fluoride emissions intensity remains below the world's average of the pre-bake technologies, which is 0.52 kg F_t/t Al [3].

Aluminum smelting operations are commonly complex. The dynamics of HF emissions are affected by a range of factors; increased alumina feeding [4], increased production capacity beyond the GTC gas capture capability, operational deficiencies, poor parameter control, and the gas flow rate [2, 4]. All other process variables being equal, the emission intensity may depend on the HF generation, which depends significantly on the potline current given a specific pot design.

We used advanced numerical simulations to predict HF emissions from roofing vents during specific activities. ANNs can track user activity and build a personalized database to determine patterns for specific activities. To our knowledge, this Rio Tinto plant is the first to use ANNs for modeling HF emissions based on operational and process factors.

2. The Problem Statement and Our Approach

Smelters operate under strict regulatory scrutiny for health and environmental performance [5]. If fluoride emissions exceed limits, it may restrict initiatives like amperage increase. Recent studies and growing demand from smelters have pointed to the need to map the impact of each operation on the fluoride emissions. Instead of just measuring generic emissions, as it was looked at in previous studies [4, 5, 6, 7, 8], a pragmatic approach is now required to take appropriate actions and help companies cut down the emissions intensity from the sources. Pragmatism means the inquiry of the way a specific smelter's operational context contributes to the total HF emission intensity, finding the relationship between the HF emission intensity and individual operations and process factors. Our research explores the predictive multifactorial modelling with artificial neural networks. Using supervised machine learning from multidimensional data sets can allow acknowledging patterns and taking appropriate preventive actions.

Supervised machine learning approach for gaseous HF emissions focuses on learning statistical functions from multidimensional data sets to make generalizable predictions about sources of variance in HF emissions. Such datasets cover electrolytic process, operations, operational excellence, and systemic data. The goal is to provide an understanding of why this approach is relevant for smelters, given its potentiality to increase the problem solving and decision-making capabilities related with the amperage increase and the conformity with regulatory limits.

The next chapter will be devoted to Artificial Neural Networks that were used to model the level of gaseous HF emissions as a function of systemic, structural, process, and operational factors.

establish a dashboard that played a key role in monitoring the factors that impact HF emissions and performance.

These arguments conclude the investigation and present smelters with an innovative approach using AI for complex analytics issues. Predictive modeling benefits from ANNs by enabling computers to make smart decisions independently. This is because they can learn and model the relationships between input and output data that are nonlinear and complex. Advanced analytics can be made easier for aluminum smelters by combining this ANN technology with other knowledge in aluminum electrolysis.

7. References

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