Proceedings of the Canadian Society for Mechanical Engineering International Congress
32nd Annual Conference of the Computational Fluid Dynamics Society of Canada
Canadian Society of Rheology Symposium
CSME-CFDSC-CSR 2025
May 25–28, 2025, Montréal, Québec, Canada

Machine Learning-Based Optimization of Tempering Parameters in Steel Manufacturing Using Industrial Electric Furnaces

Sajad Mirzaei[1*], Jean-Benoit Morin[2], Mohammad Jahazi[1*]
[1]Department of Mechanical Engineering, École de technologie supérieure (ÉTS), Quebec, Canada
[2]Finkl Steel, Sorel, Quebec, Canada
*e-mail address: Sajad.Mirzaei.1@ens.etsmtl.ca, Mohammad.Jahazi@etsmtl.ca.

Abstract

Tempering is a crucial step in steel manufacturing, designed to refine mechanical properties such as hardness through precise thermal control. With the increasing adoption of industrial electric furnaces, optimizing the heat treatment process for large-scale forging ingots has become more challenging [1]. One of the primary concerns is achieving thermal uniformity that can impact the final product's quality. Traditional trial-and-error approaches for adjusting tempering conditions are time-consuming and energy-intensive, particularly in modern furnace operations. Machine learning (ML) offers a data-driven alternative for optimizing tempering parameters, improving process reliability and efficiency. The tempering process primarily depends on two key parameters: temperature and duration. These factors are influenced by multiple variables, including material composition, geometric shape, dimensions, and ingot weight. Given the complexity introduced by these variations, determining optimal tempering conditions for new ingots remains a challenge. However, historical production data provide a valuable foundation for predictive modeling.

A dataset comprising approximately 1,100 tempered forging ingots was collected over a year from 193 m^3 industrial electric furnaces operated by an industrial partner [2]. It includes 26 steel grades—such as A182, 8630, and 4140—ingot weights ranging from 0.5 to 32 tons, and lengths varying between 0.5 and 8 meters. Two geometric types, cylindrical and rectangular cuboid ingots, were also considered. Statistical analysis, including distribution and skewness assessments, was performed using Python to identify key trends. Among various ML models evaluated, the CatBoost regression model demonstrated superior performance in predicting tempering temperature and duration. CatBoost, a gradient-boosting algorithm optimized for structured data, effectively handles categorical variables without extensive preprocessing. The model was trained using an 80%-20% train-test split, with hyperparameter tuning via grid search to optimize model configuration. Training and testing on a 12-core 4GHz CPU took approximately 62 minutes. Post-processing included SHAP (Shapley Additive Explanations) analysis to assess feature contributions and calibration plots to validate model stability.

The final model achieved an R^2 score of 0.86 for predicting tempering temperature and 0.75 for tempering duration, demonstrating acceptable reliability despite the complexity and inherent noise present in real-world industrial datasets. This ML framework provides a practical decision-support tool for optimizing tempering parameters in industrial electric furnaces. Furthermore, analysis revealed that material composition is the dominant factor in determining tempering temperature, outweighing all other parameters by nearly fivefold. In contrast, tempering duration is primarily influenced by ingot thickness, followed by shape, highlighting model ability to capture the critical importance of temperature uniformity.

1. Mirzaei, S., et al., *Influence of Heating Elements Layout on Temperature Uniformity in a Large Size Heat Treatment Furnace.* Case Studies in Thermal Engineering, 2024: p. 105062.
2. Finkl Steel Inc. *Sorel Forge*. 2021; Available from: http://www.sorelforge.com/.