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Bootstrapping Regression Support Tool for Energy Management in Induction Melting Processes: a Multi-Plant Case Study

A. Stawowy [a, *], R. Wrona [b], M. Sawczuk [b, c]
[a] AGH University of Krakow, Faculty of Management, Poland
[b] Modus Sp. z o.o., Poland
[c] Cornell University, School of Civil and Environmental Engineering, USA
* Corresponding author: E-mail address: astawowy@agh.edu.pl

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Abstract

Efficient energy management is a basis of operational quality in the foundry industry, where induction melting accounts for 70–80% of total electricity costs. This study proposes a decision-support model for predicting energy consumption, developed using data from 11 industrial plants. Facing the challenge of a small dataset, a bootstrap regression approach was employed to ensure robust estimation of Energy Performance Indicators (EnPIs). The resulting model shows high explanatory power and yields statistically significant coefficients for all variables. The model identifies key managerial and technical drivers, such as charge contamination, packing density, and organisational heat loss (furnace temperature). Unlike purely technical models, this approach utilises semi-annual aggregated data, making it a strategic tool for energy budgeting and benchmarking. The model's predictive power was externally validated against a 12th foundry, yielding a precision of 98,4%, thus proving its reliability for managerial forecasting and carbon footprint auditing in the framework of ISO 50001 standards.

Keywords: Electrical energy consumption, Melting process in iron foundry, Decision support models, Bootstrap method, Regression analysis

1. Introduction

Rising electricity prices, increasing environmental awareness, and new regulations have made proper energy management a key factor in businesses' success and profit generation [1]. This is especially true for energy-intensive industries, such as the foundry sector. Manufacturing companies must consider the cost of energy and its sustainable consumption. This consideration is crucial in energy-intensive industries, where the overwhelming majority of energy use arises from production processes, whereas consumption related to infrastructure and maintaining the operational capacity is relatively less important [2].

Cast iron foundries, classified as energy-intensive industry, are significant consumers of energy and major emitters of greenhouse gases. Traditional foundries, which utilize cupolas for producing liquid metal, have been observed to generate substantial direct emissions (Scope 1) due to coke combustion applied in the process. Conversely, modern iron foundries, which employ induction furnaces, consume substantial amounts of electricity, thereby rendering their carbon footprints largely related to Scope 2 emissions (indirect emissions derived from purchased electricity). Both traditional and modern foundries also produce Scope 1 emissions from processes not related to the liquid metal production, primarily from natural gas or LPG utilized in auxiliary heating and heat treatment systems, as well as from the decomposition of binders during core making and moulding. In the current work, the authors have focused on the management of energy and carbon footprints in foundries equipped with induction furnaces and automated casting lines. In such foundries, the most energy-intensive stage of production is the process of melting the metal charge in induction furnaces, which accounts for 70-80% of the company's total electricity consumption [3, 4]. Figure 1 presents a power distribution tree in a typical foundry.

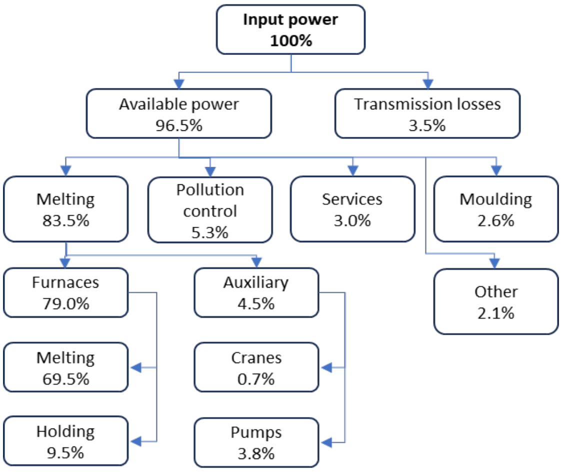

Fig. 1. Power distribution in a typical foundry. Source: [3]

The objective of this study is not only to develop a predictive model that enables decision-makers to forecast electricity consumption required to produce 1 Mg of liquid metal in a specific production plant, but also to create a general model that facilitates in-depth understanding of the organizational and technical factors influencing energy consumption in the melting process. Moreover, such a model can serve as valuable tool in managing the carbon footprint in iron foundries. Modern foundries are increasingly adopting formal Energy Management Systems (EMS) according to the ISO 50001 standard. A core requirement of this framework is the establishment of Energy Performance Indicators and energy baselines to track efficiency improvements over time.

After this introduction, a detailed description of the models and procedure used in our study is given. Section 3 presents the results of our approach. Section 4 contains the conclusion, followed by the references.

2. Assumptions and method

In the context of rising energy costs and environmental requirements, optimizing electricity consumption in the melting process is becoming increasingly important. The theoretical energy consumption (enthalpy) for melting 1 ton of metal charge to a temperature of 1500°C is 390 kWh. In practice, the melting of the components requires 500–560 kWh of electricity per ton, with 80-85% of this energy allocated to the melting process and the remainder expended as waste heat (primarily through radiation from the surface and in water cooling systems for the coils). Moreover, various additional losses may arise from suboptimal process management. Consequently, the energy consumption for melting 1 ton of metal charge can reach approximately 700 kWh, as demonstrated in Table 1.

Table 1.
Energy consumption for melting cast iron up to 1500°C

Energy requirement	Power use kWh/t
Baseline energy requirement for melting	
1. Melting enthalpy	390
2. Thermal and electrical losses	135
Total:	525
Potential losses due to the process management	
1. Sand in the charge material	25
2. Rusty charging material	30
3. Inappropriate packing density	25
4. Carburizing after melting	5
5. Melting with 50% of the power density	20
6. Melting with sump	25
7. Holding for more than 20 min with open exhaust	15
8. Unthrottled exhaust gas suction	8
9. Unnecessary overheating by 50°C	20
Total:	173
Possible total consumption:	698

Source: [4]

2.1. Previous works

There is little literature on the management of metal melting in induction furnaces. In industrial practice, routine procedures are usually applied, often based on tacit knowledge and not supported by systematic scientific research. The lack of research-based good manufacturing practices may result in failure to meet the technological parameters of metal and castings, the need to correct the composition of elements, as well as in extended melting times (and thus excessive energy consumption and consequently a suboptimal carbon footprint).

Typical errors and irregularities in the melting process are presented in Table 1 (based on [4]). Similar causes of excessive energy consumption are reported in other publications [5, 6] and in the guidelines for best practices [7, 8]. The authors of these works assert that their conclusions are based on research conducted in numerous foundries. However, they do not provide any cause-and-effect relationships expressed in terms of quantitative formulas. Even relatively recent studies [9, 10] are non-quantitative and rely primarily on reviews of the technical literature and discussions with the subject matter experts. In the case of a quantitative study [11] published in 2021, the findings are derived from sample sizes that are too limited to support definitive conclusions. It is also important to note that the data presented in Table 1 may not reflect the most recent advancements in the field. Induction furnace technology undergoing substantial progress, particularly in the realm of process control, which can present a major impact on process efficiency.

In recent years, there has been an increasing number of studies focused on carbon footprint management in various areas of the economy, including iron casting. While the primary objective of decision-making is typically to reduce the carbon footprint, this goal is directly related to the rationalisation of electricity consumption. Studies indicate that key process parameters – melting pattern, temperature profile, scrap ratio, fuel or electricity source, and operator practices – substantially influence carbon outcomes and electricity consumption. Two publications are particularly worth noting in this context.

Abdelshafy et al. [12] underscore the intricate interrelationships between the environmental, technical, and economic dimensions of cast iron production. With regard to the materials employed, the results indicate that augmenting the quantity of steel scrap leads to a substantial decrease in CO_2 emissions. It has been determined that an alloy composition containing 25% steel scrap results in a minimum carbon footprint of 650 kg CO_2 eq./ton. However, further increase in the steel scrap content results in higher carbon footprints and production costs due to the additional materials (ferrosilicon and carburizing agents) required to maintain the alloy composition.

The goal of Howard et al. [13] was the identification of best-practice melting patterns and carbon/energy optimization in induction furnaces. They used time-series K-means clustering combined with multi-criteria decision-making and operational data analysis to develop the best pattern. The authors report that best-practice melting patterns yield 0.5 metric tons of CO_2 per ton of casting and an 8.6% reduction in electricity cost.

2.2. Method

A structured questionnaire was disseminated to 25 large and medium-sized iron foundries in Poland. The survey requested operational data averaged over the first half of 2025, specifically regarding: direct electricity consumption for melting a standard alloy, furnace power and capacity, melting time, charge composition shares, metallurgical yield, and packing density. Additionally, respondents provided qualitative comments on the organizational aspects of their melting processes. Out of 14 responses received, two were incomplete and one contained significant outliers; thus, a final dataset of n=11 plants was used for the analysis.

Due to the limited sample size and the non-normality of the input distributions, a non-parametric bootstrapping method was employed to develop the regression model. To the best of the authors' knowledge, this study is the first to apply the bootstrapping approach for forecasting and energy management purposes in the foundry industry.

Regression analysis is the most used statistical tool for analysing dependences. The classical Ordinary Least Squares (OLS) is not always a satisfactory solution when working with small samples or datasets containing outliers. In such cases, the regression bootstrap introduced by Efron [14], emerges as both an appropriate and effective tool. The fundamental principle of the bootstrapping method is to generate a substantial number of subsamples through the random selection of observations from the original dataset, with these subsamples being drawn with replacement. Each subsample is then used to calculate the statistics of interest.

In this study, we consider a linear regression model of the form $\boldsymbol{Y} = \boldsymbol{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}$, where $Y = (Y_1,\ldots,Y_n)$ is a dependent variable, $X = (x_{ij})$; $i = 1,\ldots,n$; $j = 1,\ldots,k$; is a design matrix, $\beta = (\beta_1,\ldots,\beta_k)$ is a vector of unknown regression coefficients, and $\varepsilon = (\varepsilon_1, \ldots,\varepsilon_n)$ is a vector of residuals, n is the sample size.

The process of bootstrapping is comprised of the following steps [15]:

1. Fit regression model using the original dataset,
2. From the original sample, draw random sample with size n,
3. Compute statistic θ from the resample in 2: θ_1^*,
4. Repeat steps 2 and 3 B times (e.g. 1000 or more iterations), get B statistics of interest: $\{\theta_1^*, \theta_2^*,\ldots, \theta_B^*\}$,
5. Compute moments, standard errors, confidence intervals, etc. for these B statistics.

A significant benefit of bootstrapping is its ability to construct confidence intervals without assuming asymptotic normality [15]. The most popular – percentile method – utilizes the distribution of bootstrapped estimates for the construction of confidence intervals. Consider a coefficient β_j with an empirical bootstrap distribution $\{\beta_{j1}^*, \beta_{j2}^*,\ldots, \beta_{jB}^*\}$. The 95% confidence interval is obtained in the following steps:

1. Sort the bootstrap estimates $\{\beta_{j1}^*, \beta_{j2}^*,\ldots, \beta_{jB}^*\}$ in ascending order,
2. Take the 2.5th percentile as the lower bound $Q_{0.025}$,
3. Take the 97.5th percentile as the upper bound $Q_{0.975}$,
4. The interval is $[Q_{0.025}, Q_{0.975}]$.

While advanced machine learning models, such as Random Forest (RF) or Support Vector Machines (SVM), were initially considered, they were deemed unsuitable for this study. At a sample size of n=11, such "black-box" models are highly prone to overfitting and lack the transparency necessary for managerial decision support. Linear regression with bootstrap resampling remains the most robust and interpretable method for this context, providing stable coefficient estimates and reliable confidence intervals that are essential for energy benchmarking.

3. Results

This chapter presents the results of our study on the proposed regression model. First, basic descriptive statistics for the collected dataset are presented. Next, the research procedure, the model obtained, and a discussion of the results are provided.

3.1. Data

The primary challenge in industrial studies of this nature is the acquisition of a sufficiently large and representative dataset. For a classical linear regression model with nine explanatory variables, a sample of approximately 125–135 observations is typically required to ensure statistical power and reliability [16]. In the practice of industrial surveys, collecting such a large sample is impossible: more than half of respondents do not respond at all, and some of the responses are incomplete or incorrect [17].

The variables considered in this study include:
dependent variable:
ec – electricity consumption for melting 1 tonne of a standard alloy [kWh/t],
explanatory variables:

pc – installed power per tonne of furnace capacity [kW/t],
mt – melting time per tonne of a standard alloy [min],
sc – share of cast iron scrap (own and external) in the charge [%],
sp – share of pig iron in the charge [%],
ss – share of steel scrap in the charge [%],
cc – charge contamination [%],
te – temperature of the empty furnace before the next melt per tonne of furnace capacity [°C/t],
pd – packing density of the charge [t/m^3],
nc – number of crucibles.

The model initially intended to account for the heel (liquid residue) effect; but this was excluded as only one participating plant employed this practice. Furthermore, charge contamination (*cc*) was quantified using the metallurgical yield (the ratio of liquid metal weight to cold charge weight), calculated as 100% minus the metallurgical yield.

To ensure the model's interpretability and physical validity, the selection of explanatory variables was based on a structured approach that systematically addresses two distinct criteria: (1) evaluating the potential magnitude of a variable's causal impact on energy consumption based on domain expertise, and (2) identifying and omitting redundant variables that exhibit strong multicollinearity. The first criterion was addressed via an Expert-based entry method, where predictors were selected based on established foundry engineering literature and practical operational knowledge [4, 5, 6], rather than relying on automated statistical selection procedures (e.g., stepwise regression). Automated methods in small-sample contexts ($n < 30$) often lead to overfitting or the artificial exclusion of physically essential variables [18].

The second criterion – the isolation and removal of redundant, highly correlated inputs – was addressed sequentially through a comprehensive correlation analysis of the pre-selected candidate variables. This two-step screening process ensures that the final model is both physically and structurally valid.

The correlation analysis mostly revealed weak dependencies, with four notable exceptions. A strong correlation was observed between empty furnace temperature (*te*) and melting time (*mt*) (Pearson r = 0.86). This is considered a confounding relationship influenced by furnace capacity; both variables were retained due to their distinct roles in the heat balance and organizational efficiency.

Significant correlations were also found between pig iron share (*sp*) and packing density (*pd*) (r = 0.88), steel scrap share (*ss*) and packing density (r = -0.77), and between pig iron and steel scrap shares (r = -0.81). This interdependency stems from the complementary nature of the charge: since the share of cast iron scrap (*sc*) is often fixed by technological constraints, the shares of pig iron and steel scrap are inversely proportional (together with *sc*, they constitute approximately 98% of the charge). To prevent multicollinearity while maintaining predictive power, steel scrap share (*ss*) was selected over pig iron share (*sp*), as *ss* exhibited a significantly stronger correlation with the dependent variable (r = -0.78 vs. r = 0.59). In turn, the variable *sc* was not included in the model due to the weakest correlation with the dependent variable among all independent variables (r = -0.11). Consequently, the final model focuses on *ss* and *pd* as the primary indicators of charge physical characteristics.

The distribution of the input variables deviates from normality, characterized by distinct clustering and mean values that are skewed within their respective intervals. This is most prominent for the *mt* (melting time) variable, where observations cluster near the minimum and maximum values rather than around the mean. These characteristics further justify the use of non-parametric bootstrapping to ensure robust parameter estimation. Table 2 shows basic statistics for the collected data.

Table 2.
Descriptive statistics of the dataset

Variable/statistics	min	max	mean
ec	460.0	720.0	581.2
pc	571.0	1000.0	723.7
mt	6.4	30.0	14.6
sc	32.5	60.5	45.4
sp	0.0	43.8	20.5
ss	11.9	50.0	29.5
cc	1.2	9.0	3.7
te	100.0	550.0	253.6
pd	1.6	3.0	2.2
nc	1	2	

3.2. Model

Table 3 presents the regression model for the original dataset ($n = 11$).

Table 3.
Basic regression model

var	β_j	se	p-value	lower 95%	upper 95%
intercept	214.99	181.04	0.32	-361.15	791.14
pc	0.40	0.10	0.03	0.07	0.72
mt	5.62	2.27	0.09	-1.61	12.85
cc	26.60	4.49	0.01	12.30	40.90
ss	-4.18	1.30	0.05	-8.32	-0.04
pd	56.49	45.49	0.30	-88.28	201.26
te	-0.18	0.13	0.26	-0.60	0.24
nc	-34.58	22.37	0.22	-105.78	36.61

R^2	R^2_{adj}	SE	F	sig. of F
0.981	0.936	21.067	21.928	0.014

The multiple regression model demonstrates a very high overall fit (R^2_{adj} = 0.936) and a statistically significant F-test ($p = 0.014$), indicating that the selected explanatory variables collectively explain a substantial proportion of the variance in electricity consumption. However, the limited sample size affects the reliability of individual parameter estimates; four coefficients failed to reach statistical significance ($p > 0.05$), two were marginally significant, and only two showed strong significance ($p < 0.04$). This suggests potential overfitting and low statistical power in a classic method, further justifying the necessity of the bootstrapping approach outlined in Section 2.2.

To implement the bootstrap method, a custom macro was developed in VBA (Visual Basic for Applications) for MS Excel. The procedure followed these steps:

1. Resampling. A bootstrap sample of size n = 11 was drawn with replacement from the original dataset. To ensure high-quality randomization, the Taillard generator [19] was employed. This generator is noted for its long period and the ability to be initialized with a specific seed value, ensuring that the results are fully reproducible.
2. Model fitting. The ATPVBAEN.XLAM!Regress module was programmatically called to fit the regression model for each resample and store the resulting coefficients and statistics.
3. Iterations. Preliminary simulations indicated that B = 1000 iterations were sufficient to achieve stable and reliable estimates for the bootstrap distributions.

Due to the stochastic nature of bootstrapping, the entire 1000-iteration process was repeated 50 times, and the model with the smallest forecast error was selected as the final solution. The regression coefficients, standard errors, confidence interval and other statistical data were analysed manually using standard Excel functions. It should be emphasised that using a custom solution offers a higher degree of flexibility compared to employing off-the-shelf packages such as Statistica or SPSS, as it allows full control over all parameters of the process. In particular, any bootstrap resamples yielding an R^2 of 1.0 were excluded from the analysis; such cases occurred when a resample contained too many identical observations, leading to a spurious perfect fit that does not reflect the underlying physical process.

The analysis of these 50 independent bootstrap runs demonstrated the high stability of the method. The standard error SE of the model across all runs remained within a narrow range (min = 22.42, max = 24.23), with a mean value of 23.48 and a low standard deviation SD = 0.42. Similarly, the F-statistic was consistent across runs (mean = 18.09, SD = 0.57). This level of consistency confirms that the bootstrap estimates are robust and not overly sensitive to the randomization seed, providing a reliable foundation for managerial decision-making.

Table 4 shows the best-performing bootstrap regression model.

Table 4.
Bootstrap regression model

var	β^*_j	se	p-value	lower 95%	upper 95%
intercept	211.00	297.79	$<10^{-4}$	-240.29	681.74
pc	0.41	0.14	$<10^{-7}$	0.16	0.66
mt	6.58	4.33	$<10^{-5}$	1.43	14.46
cc	26.50	14.17	$<10^{-6}$	11.79	41.77
ss	-4.11	2.53	$<10^{-6}$	-8.31	0.39
pd	51.39	83.21	$<10^{-4}$	-30.49	170.84
te	-0.23	0.29	$<10^{-4}$	-0.79	0.25
nc	-32.81	45.32	$<10^{-4}$	-99.33	26.29

R^2	R^2_{adj}	SE	F	sig. of F
0.976	0.920	22.420	19.439	0.017

3.3. Discussion of the results

The results of the bootstrap method demonstrate high model quality: the parameter values are consistent with the initial regression model, but the effectively larger resampled dataset ensures that all regression coefficients are highly significant ($p < 0.0001$). From a managerial perspective, the resulting equation functions as a normalized Energy Performance Indicator. By comparing actual consumption with the model's predictions, energy managers can identify operational anomalies and evaluate the impact of technological changes.

The model yields the following quantitative insights:

1. Increasing furnace power by 1 kW/t corresponds to an increase in specific consumption by 0.41 kWh/t.
2. Each additional minute of melting time increases consumption by 6.58 kWh/t.
3. A 1% increase in charge contamination results in an increase in energy consumption for melting the charge by 26.50 kWh/t.
4. Increasing the steel scrap share by 1% reduces energy demand by 4.11 kWh/t.
5. A 1 t/m^3 increase in packing density raises consumption by 51.39 kWh/t.
6. Increasing the pre-melt furnace temperature by 1°C/t reduces demand by 0.23 kWh/t.
7. Single-crucible systems are, on average, 32.81 kWh/t more energy-intensive than double-crucible systems.

Possible explanations for the above findings are presented below.

Ad 1. Furnace power vs. efficiency.

The positive correlation between installed power *pc* and energy consumption may seem counterintuitive, as higher power typically shortens melting time and reduces thermal losses. However, in an industrial setting, this finding likely points to underutilization of high-power assets. Oversized furnaces operating below their nominal capacity, or those poorly synchronized with the casting line, suffer from disproportionately high cooling and auxiliary losses. Furthermore, high-power systems may experience greater electromagnetic turbulence, which, if not managed through precise process control (e.g., keeping lids closed), leads to increased radiation losses.

Ad 2 & 3. Time and contamination.

The impact of melting time is a direct consequence of cumulative heat losses (conduction through the lining and radiation). The findings for contamination (26.50 kWh/t) align with literature [4], where sand residues and oxides act as heat sinks, requiring additional enthalpy for slag formation.

Ad 4 & 5. Charge composition and density.

While literature often suggests that higher packing density improves efficiency, our model indicates the opposite for this specific industrial cluster. This can be explained by the electromagnetic penetration depth effect. A high-density charge in these plants is typically associated with a high share of pig iron and small-diameter scrap. If the inverter frequency is not perfectly tuned to these smaller fragments, the electrical efficiency drops because the induction effect is less effective than with larger, optimally spaced scrap pieces. Therefore, the negative coefficient for steel scrap (*ss*) combined with the positive for density (*pd*) suggests that larger, less-dense steel scrap fragments are more energy-efficient for the specific equipment configurations used in the surveyed foundries.

Ad 6. Thermal integration.

The impact of the emptied furnace temperature (*te*) reflects the quality of production scheduling. A higher *te* indicates a well-synchronized furnace-casting cycle, where the crucible does not cool down excessively between heats. This waste heat recovery in the lining reduces the total enthalpy required for the subsequent melt.

Ad 7. System configuration.

The superior efficiency of double-crucible systems ($nc = 2$) is a significant managerial finding. Such systems offer higher operational flexibility and better power utilization factors. While single-crucible furnaces are simpler, they often force the power supply to idle or operate at reduced power during slagging or pouring, whereas double-crucible setups allow for continuous energy transfer to the metal, significantly improving the overall energy-to-metal ratio.

3.4. Model validation and predictive performance

To evaluate the model's ability to generalize to new industrial environments – a key requirement for its application as a managerial decision-support tool – an external validation was conducted. Data from an additional foundry located in eastern Poland were used for this purpose. Crucially, these data were acquired after the model development phase and were not part of the training dataset. The operational parameters for this plant were: $pc = 750.0$, $mt = 12.0$, $cc = 2.0$, $ss = 30.0$, $pd = 2.3$, $te = 225.0$, and $nc = 2$.

The actual electricity consumption recorded by this foundry was 520 kWh/t. The prediction generated by the bootstrap model was 528.3 kWh/t, representing a remarkably low deviation of only 1.6%. This high level of accuracy on external, out-of-sample data confirms that the model is not overfitted and possesses the robustness required for industrial energy auditing and strategic forecasting within the ISO 50001 framework.

4. Conclusions

The study demonstrates that bootstrap regression is a robust and suitable method for modeling unit electricity consumption in induction melting under small-sample industrial conditions. In the contemporary era of big data, the necessity to model processes based on limited datasets remains a critical challenge across various domains, including specialized manufacturing, medicine, and the natural sciences. By producing stable coefficient distributions, the proposed approach addresses this challenge and effectively eliminates the issues of low statistical power and overfitting inherent in classical OLS when dealing with limited data.

The research provides a reliable framework for strategic energy management in foundries through the following key findings:

1. Managerial utility. The developed model can serve as a high-level benchmarking tool, allowing managers to distinguish between unavoidable thermodynamic requirements and organizational inefficiencies.
2. Supply chain and quality control. Identifying charge contamination and packing density as primary energy drivers provides actionable insights for supply chain management and the rigorous quality control of raw materials.
3. Operational policy. The significance of variables such as the number of crucibles and furnace temperature highlights the critical impact of production scheduling. Minimizing furnace downtime is shown to be a direct and effective energy-saving strategy rather than just a logistical goal.
4. Validation and standardization. The successful external validation on an independent foundry, yielding an error of less than 1.6%, confirms the model's reliability. The robustness of this approach proves its practical utility for energy auditing, baseline setting, and verifying energy-saving targets within the ISO 50001 framework.

While the current model, based on semi-annual aggregated data, provides a valuable tool for sector-wide benchmarking and strategic planning, further research is required to analyze real-time operational variations. Future studies will focus on transitioning from macro-level indicators to high-frequency, heat-by-heat data collected directly from individual melting cycles.

The authors are currently engaged in a research project at a large Polish foundry, where a dataset comprising several hundred individual melt records is being collected. This will enable the development of accurate models using both classical regression and advanced Machine Learning methods. However, it is important to emphasize a key trade-off: while large-scale, single-plant models offer extreme precision for a specific facility, they are often difficult to transfer to other plants due to unique equipment configurations. In this context, the approach presented in this paper (utilizing averaged multi-plant data) remains superior for developing universal industry benchmarks and supporting broader energy policies in the metal casting sector.

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