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An AI-driven framework for efficient and accurate calibration of electricity meters using extreme gradient boosting

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ABSTRACT

Calibration testing plays a vital role in electricity meter manufacturing to guarantee measurement accuracy and compliance with industry standards. In practice, however, conventional calibration methods are often hindered by lengthy test cycles and the high cost of expanding test bench capacity. This study proposes a data-driven approach to address these limitations by applying machine learning techniques to optimize calibration testing. An extreme gradient boosting (XGBoost) regression model, enhanced through systematic hyperparameter tuning and feature engineering, was developed to predict calibration outcomes using data obtained from existing production test benches. When evaluated under real manufacturing line conditions, the proposed method shortened calibration runtime by about 55% compared with manual procedures relying on power supply units (PSU) and standard meter calculations, while maintaining reliable measurement accuracy. The framework also achieved lower root mean square error (RMSE), demonstrating improved predictive performance. In addition to reporting these results, the study describes the preprocessing pipeline, model selection process, and optimization strategy, providing a practical and replicable framework for integrating artificial intelligence (AI) into industrial calibration processes.

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1. INTRODUCTION

The manufacturing of electricity meters is a vital industry, where accuracy and reliability are critical to ensure fair and precise billing for consumers [1]. At the center of this process lies calibration testing, which verifies the accuracy of meter readings against a standard reference bench. This step is not only a technical necessity but also a regulatory requirement, as it ensures compliance with national and international standards. Despite its importance, calibration in its traditional form remains highly time-consuming and labor-intensive, creating significant challenges for manufacturers that must balance strict accuracy requirements with the need for efficient, large-scale production.

Traditional calibration methods require each meter to be tested individually, often under multiple load conditions, and compared against a standard reference bench. While this guarantees measurement accuracy, it becomes a serious bottleneck in high-volume manufacturing environments. For instance, facilities that produce thousands of meters daily face prolonged calibration cycles, which directly constrain throughput and delay delivery schedules. To cope with this demand, manufacturers often expand capacity by investing in additional test benches. However, this approach introduces several new problems: the acquisition and maintenance of benches represent a substantial financial burden, the need for additional skilled operators increases labor costs, and the physical space required for large test bench installations creates logistical difficulties. These combined factors make scaling production both costly and inefficient, particularly in a competitive market where flexibility and responsiveness are critical.

Given these limitations, there is growing interest in adopting advanced technologies—particularly artificial intelligence (AI)—to improve calibration efficiency. Intelligent calibration has already been explored in diverse domains, such as micro-electro-mechanical systems (MEMS) sensor fusion [2], [3], strapdown inertial navigation systems (SINS) [4], vortex flowmeter calibration [5], and even algorithmic music composition [6]. These studies demonstrate how machine learning models, especially regression-based approaches, can provide faster and more accurate predictions than traditional calibration techniques. However, despite the evident benefits, the application of intelligent calibration in electricity meter manufacturing remains limited. One notable contribution is the framework proposed by Zaidan *et al.* [7], which employed automated test systems and interchangeable virtual instruments (IVI) for rapid calibration. While promising, such approaches have yet to be fully adapted for electricity meter production, where the volume and complexity of calibration data present both challenges and opportunities for AI-driven solutions.

Among available techniques, tree-based models such as extreme gradient boosting (XGBoost) have shown considerable potential in handling large-scale, complex datasets. XGBoost, in particular, is widely recognized for its predictive power and efficiency, outperforming alternatives such as support vector machines (SVM), decision trees (DT), and gradient boosting decision trees (GBDT) in a variety of applications [8]–[10]. Its ensemble approach, which combines multiple weak learners into a robust predictive model, allows it to deliver high accuracy while mitigating overfitting through integrated regularization [11], [12]. Furthermore, XGBoost is well-suited for industrial applications due to its efficient memory use, ability to manage missing data, and scalability across distributed computing platforms [13], [14]. These characteristics make it particularly relevant to electricity meter manufacturing, where vast amounts of calibration data are generated daily. To achieve optimal results, however, XGBoost requires careful hyperparameter tuning to balance accuracy and generalization. Fine-tuning these parameters is complex, especially when dealing with high-dimensional datasets typical of manufacturing environments. Recent studies across engineering, energy, and manufacturing domains have demonstrated the strong predictive capability of XGBoost and the benefits of systematic model optimization [15]–[23]. In particular, optimization strategies such as particle swarm optimization (PSO) have proven effective for efficiently searching suitable hyperparameter configurations [24]–[26]. By integrating XGBoost with PSO-based optimization, it becomes possible to develop an intelligent calibration framework that not only reduces calibration time but also minimizes reliance on costly test bench infrastructure and decreases operational expenses.

This study investigates the integration of XGBoost with PSO-driven optimization to create a scalable calibration system for electricity meter manufacturing. The goal is to streamline calibration, enhance production throughput, and improve cost-effectiveness without compromising accuracy or compliance. By automating and refining this essential step, the proposed approach offers a pathway toward smarter, more efficient manufacturing practices that can better respond to evolving market demands.

2. METHOD

2.1. Research framework

The research framework for the development of an intelligent calibration verification test system aims to predict accurate test metrology in electricity meter manufacturing. The framework, shown in Figure 1, is grounded in a literature review that establishes the baseline for the research. The problem addressed in this study pertains to the calibration testing process in the electricity meter manufacturing industry, specifically the metrology challenges associated with standard calibration test benches. The traditional calibration process requires comparing the meter under test to a standard meter test bench, a time-consuming procedure with long cycle times [27]. Increasing production capacity would typically necessitate additional expensive test benches, creating a financial burden. The research hypothesis suggests that machine learning can provide a solution by predicting accurate calibration results, thus eliminating the need for additional test benches. Based on this, a predictive model using machine learning is developed to automate and optimize the calibration verification test process.

2.2. Data collection

The data collection process in this study centers on calibration test results sourced from meter test bench machines utilized during manufacturing. The dataset comprises meter readings, test parameters such as voltage and current, and associated calibration outcomes, including recorded error values. These data points, drawn from the internal machine database, represent a wide range of meter models and testing conditions, capturing the diversity inherent in the production environment. To align with industry standards, all calibration results conform to the accuracy thresholds defined for standard-class meters.

In addition to the primary data, supplementary information such as production line identifiers and environmental variables (e.g., temperature and humidity) was incorporated where available to evaluate their influence on calibration performance and strengthen model reliability. Before modeling, the dataset underwent a systematic preprocessing phase: missing values were addressed using mean or mode imputation, outliers were capped via the interquartile range (IQR) method, and features were normalized using min-max scaling. Irrelevant attributes (e.g., timestamps) were excluded, and interaction features—such as voltage-current pairs—were engineered to improve predictive capacity. Feature selection was guided by correlation analysis and mutual information scores. For model training and evaluation, the dataset was divided into an 80:20 ratio, ensuring robust testing on previously unseen data.

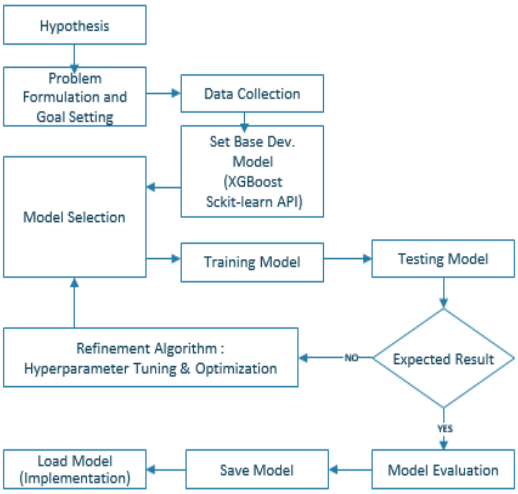

Figure 1. The research framework for intelligent calibration verification test system

2.3. Model development using XGBoost

With the dataset properly prepared, the next step involves training the XGBoost model. This algorithm builds its predictive strength through an ensemble of DT, where each successive tree is designed to correct the residual errors left by its predecessors. In every iteration, a new DT is constructed using the gradient of the loss function, which quantifies the difference between predicted and actual values. This gradient boosting mechanism allows the model to iteratively refine its performance by reducing prediction errors over time. The underlying mathematical structure of XGBoost centers on optimizing an objective function, which combines a loss function—measuring prediction accuracy—with a regularization term that penalizes model complexity. This combination not only enhances predictive precision but also helps prevent overfitting. The objective function is formally expressed in (1), reflecting the model's balance between accuracy and generalization.

$$L(\theta) = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{k} \Omega(f_k) \quad (1)$$

Where:
- $l(y_i, \hat{y}_i)$ is the loss function (e.g., mean squared error) for the predicted and actual values.
- $\Omega(f_k)$ is the regularization term, which penalizes complexity in the model to prevent overfitting.
- K represents the number of trees.
- f_k represents the DT in the model.

In this study, model performance was assessed using root mean square error (RMSE), mean absolute error (MAE), and the coefficient of determination (R^2). RMSE and MAE capture the average magnitude of prediction errors, while R^2 measures how well the model explains variance in the target variable. To ensure robustness, a five-fold cross-validation procedure was applied. To validate the choice of XGBoost, its performance was compared with support vector regression (SVR), random forests (RF), and linear regression (LR). The experimental results are presented in Table 1.

As shown in Table 1, XGBoost consistently outperformed the alternative models across all evaluation metrics. Compared to RF and SVR, XGBoost achieved lower error rates (RMSE=0.118, MAE=0.095) and a higher R^2 value (0.921), indicating stronger explanatory power and predictive accuracy. Its performance advantage is largely attributed to its regularization framework, which effectively controls model complexity, and its ability to handle outliers and missing values within the calibration dataset. These results demonstrate that XGBoost is not only capable of delivering more accurate predictions than conventional models but is also better suited for the diverse and complex datasets typically encountered in electricity meter calibration. The findings justify its selection as the core model for the intelligent calibration framework proposed in this study.

Table 1. Comparative performance of machine learning models

Model	RMSE	MAE	R^2
LR	0.187	0.152	0.842
SVR	0.161	0.127	0.876
RF	0.142	0.114	0.892
XGBoost	0.118	0.095	0.921

2.4. Hyperparameter tuning and optimization

In this study, PSO was utilized to identify the optimal set of hyperparameters for the XGBoost model. PSO is a population-based optimization technique that simulates the social behavior of a swarm, where each particle represents a potential solution—in this case, a specific combination of hyperparameters such as learning rate, maximum depth, and the number of estimators. The algorithm iteratively updates each particle's position in the search space based on its own best-known position and the global best position identified by the swarm.

To configure the optimization, a swarm of 20 particles was initialized, and the search process was allowed to run for a maximum of 50 iterations or until convergence. These values were selected to provide a balance between exploration and computational efficiency: a smaller swarm may limit the diversity of candidate solutions, while excessively large swarms significantly increase computational cost without a proportional improvement in accuracy. Similarly, 50 iterations were found sufficient to achieve convergence in preliminary tests, as performance gains plateaued beyond this point. The search space for hyperparameters was defined as follows, based on prior research and practical constraints in calibration datasets:

- Learning rate (η): 0.01-0.3, a smaller learning rate (closer to 0.01) enables gradual convergence and reduces the risk of overshooting optimal solutions, while higher values (up to 0.3) allow faster convergence but may increase the risk of overfitting.
- Maximum tree depth: 3-10, shallower trees (depth 3-5) prevent overfitting and improve generalization, while deeper trees (up to 10) enable the model to capture complex patterns in calibration data.
- Number of estimators (trees): 50-500, this range balances computational efficiency with predictive power; too few trees may underfit, while too many can slow training without significant accuracy gains.
- Subsample ratio: 0.6-1.0, this parameter controls the fraction of training data sampled for each tree, with values under 1.0 adding stochasticity that helps prevent overfitting.
- Column sample by tree (feature sampling ratio): 0.5-1.0, sampling features introduces diversity in tree construction and reduces correlation among trees, enhancing generalization.

During each iteration, particles adjusted their velocities and positions using the standard PSO update rules presented in (2) and (3) which balance exploration and exploitation by incorporating both individual and collective learning components.

$$V_{id}(t+1) = \omega V_{id}(t) + C_1.rand(0,1).(P_{id} - X_{id}) + C_2.rand(0,1).(P_{gd} - X_{id}) \quad (2)$$

$$X_{id}(t+1) = X_{id}(t) + V_{id}(t+1) \quad (3)$$

Where:
- $V_{id}\ (t)$ is the velocity of particle iii in dimension ddd at time ttt.
- $X_{id}(t)$ is the position (hyperparameter value) of particle iii in dimension ddd.
- P_{id} is the best position (hyperparameter set) found by particle iii.
- P_{gd} is the best position found by the global swarm.
- ω is the inertia weight that controls the impact of previous velocities.
- C_1 and C_2 are cognitive and social coefficients, respectively (typically set to 1.5).
- $rand(0,1)$ is a random number between 0 and 1, adding stochasticity to the search process.

The optimization objective was to minimize the RMSE through five-fold cross-validation. This ensured that the chosen hyperparameters not only minimized prediction errors but also supported generalization to unseen data. The final hyperparameter configuration selected by PSO was a learning rate of 0.08, maximum depth of 6, 300 estimators, subsample ratio of 0.8, and column sample ratio of 0.7, which delivered the best trade-off between accuracy and computational efficiency.

2.5. Model validation

The model is validated through cross-validation to ensure its generalizability and robustness. Cross-validation helps prevent overfitting and ensures that the model can make accurate predictions on unseen data. The model's performance is evaluated using RMSE as in (4) and MAE as in (5), where n is the number of data points, y_i is the actual value, $\hat{y}_i$ is the predicted value.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{4}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{5}$$

2.6. Comparison with traditional calibration method

To evaluate the effectiveness of the proposed intelligent calibration system, a detailed comparison was conducted against the traditional manual method. Conventional calibration typically involves matching each meter’s reading to a reference device through several testing cycles, which not only demands considerable time and labor but also introduces variability due to human involvement. In contrast, the machine learning-based approach predicts calibration outcomes using a trained XGBoost model, significantly reducing the time and effort needed per meter. Multiple configurations of the model were tested to ensure robustness, including those tuned with GridSearchCV, RandomizedSearchCV, Bayesian optimization, a Bayesian-SVM hybrid, and a default model without hyperparameter tuning. These variations were compared based on prediction accuracy, processing time, and error rates. Among them, the proposed model consistently outperformed the rest, achieving the highest accuracy and lowest error, thereby demonstrating its potential to streamline the calibration process and serve as a reliable alternative to traditional methods.

2.7. Implementation steps overview

The model development process was systematically organized into a five-stage pipeline, each designed to enhance data quality and model performance. The first stage involved raw data extraction from calibration logs, which provided the foundational dataset for the study. This was followed by data preprocessing, where missing values, noise, and outliers were handled through cleaning and transformation procedures to ensure consistency and reliability. In the third stage, feature selection and creation were carried out using domain expertise to engineer variables that could significantly improve model learning and generalization. The fourth stage focused on model training, utilizing the XGBoost algorithm known for its speed and performance, in combination with PSO to fine-tune hyperparameters for optimal results. Finally, the fifth stage involved evaluation, employing cross-validation to measure model robustness and benchmarking it against both traditional and alternative machine learning methods to validate its effectiveness. As illustrated in Figure 2, this pipeline ensures a structured and efficient workflow. Tools such as Python's scikit-learn, XGBoost, and Optuna were integrated into a cloud-based Jupyter environment, enabling reproducibility, collaborative development, and scalability for future enhancements and deployment in real-world applications.

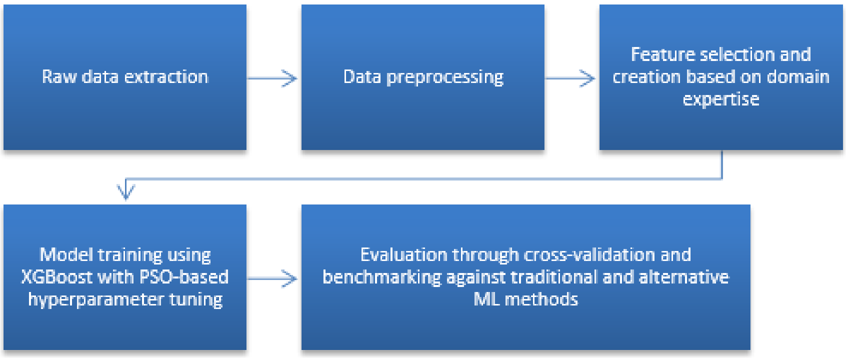

Figure 2. Model development process

3. RESULTS AND DISCUSSION
3.1. Time efficiency

The integration of AI in the calibration testing of electricity meters has demonstrated significant improvements in time efficiency, aligning directly with the goal of creating a more efficient and low-cost process for meter manufacturing. Traditional calibration methods, which rely heavily on manual input and operator judgment, are often time-consuming and prone to human error. These challenges are alleviated by AI solutions, which automate calibration processes with greater precision and speed.

Table 2 shows the significant improvement in time efficiency when using AI-driven calibration methods compared to traditional methods in electricity meter manufacturing. The table highlights the time required for calibrating one meter and the total time for 100 meters under both methods. In the traditional method, it takes 20 minutes per meter for calibration, leading to a total of 2,000 minutes for 100 meters. This process relies heavily on manual input and operator judgment, which can be slow and prone to errors. The time required for calibration is thus relatively high, resulting in increased production costs and delays. In contrast, the AI-driven method reduces the time per meter to just 10 minutes, cutting the total calibration time for 100 meters down to 1,000 minutes. AI solutions automate the calibration process, minimizing human intervention, which results in faster, more consistent, and accurate outcomes. The use of AI not only improves precision but also significantly speeds up the process, reducing the overall time spent on calibration. The time savings of 50% between the two methods demonstrates the potential for substantial efficiency gains. By integrating AI into calibration testing, electricity meter manufacturers can reduce time spent on each calibration cycle, leading to faster production, lower labor costs, and a more cost-effective manufacturing process.

Table 2. Comparison of time efficiency in calibration methods

Calibration method	Time per meter (minutes)	Time for 100 meters (minutes)	Time savings (%)
Traditional method	20	2,000	-
AI-driven method	10	1,000	50

3.2. Accuracy

The adoption of AI in calibration testing has led to substantial gains in both time efficiency and accuracy. Unlike manual approaches, which are often prone to variability and human error, the AI-based system demonstrated greater consistency in detecting calibration deviations. This improved precision results in more dependable outcomes, ultimately enhancing the reliability of the overall process. To assess the system’s performance, key evaluation metrics—RMSE and MAE—were employed, with the results illustrated in Figures 3 and 4. These metrics provide a clear indication of the model’s accuracy across various testing scenarios.

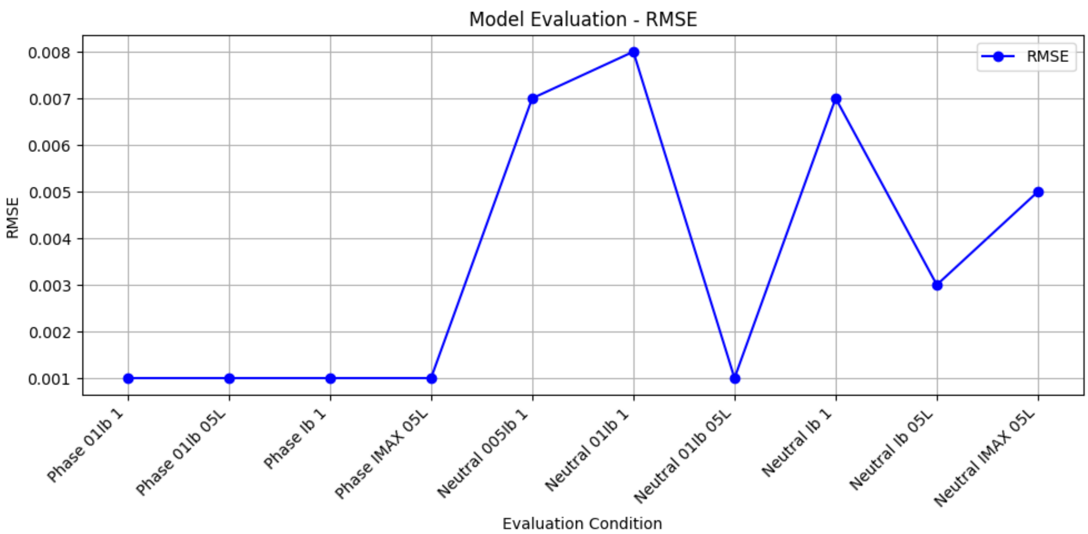

Figure 3. RSME results of AI in the calibration testing of electricity meters

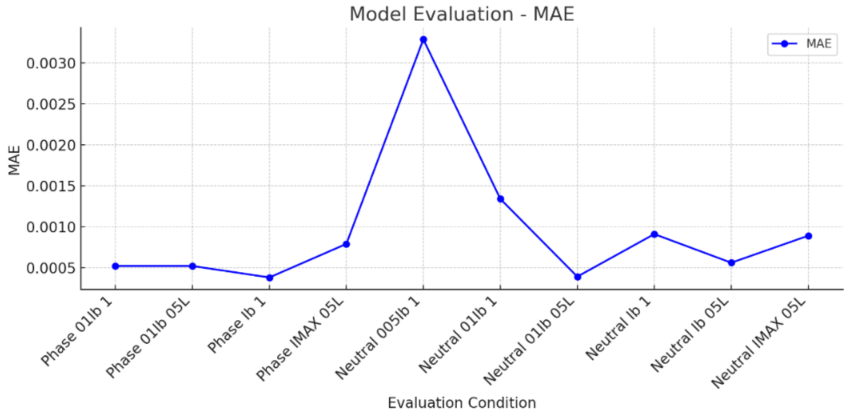

Figure 4. MAE results of AI in the calibration testing of electricity meters

Figure 3 illustrates a comparative analysis of RMSE values between the AI-driven and traditional calibration methods across multiple testing phases. RMSE serves as a crucial indicator of calibration precision, where lower values denote greater accuracy. The AI-based approach consistently records RMSE values as low as 0.001 in most phases, indicating minimal deviation from actual calibration values. In contrast, the traditional method yields higher RMSE values—such as 0.007 and 0.008—suggesting greater variability and reduced accuracy in the calibration results. What stands out in Figure 3 is the consistency of the AI model in maintaining low-error predictions across diverse testing conditions. These near-zero RMSE values not only validate the model's high predictive accuracy but also demonstrate its capacity to generalize effectively across varying scenarios. This reinforces the potential of the proposed XGBoost-based intelligent calibration system for reliable deployment in real-world manufacturing environments.

The observed disparity in RMSE underscores the clear advantage of AI in managing calibration tasks. By leveraging large datasets and advanced learning algorithms, the AI-driven method minimizes human intervention and the inconsistencies that often accompany manual processes. Traditional methods, which rely heavily on operator expertise and manual adjustments, are inherently more susceptible to error. Therefore, the consistently lower RMSE values achieved by the AI system highlight its reliability and precision—key attributes for enhancing productivity and reducing errors in electricity meter manufacturing.

Figure 4 illustrates the MAE observed in both AI-based and conventional calibration methods across multiple testing phases. As a key indicator of predictive accuracy, MAE reflects the average absolute difference between predicted and actual values—where smaller values indicate more precise calibration. The AI-based approach consistently demonstrates lower MAE figures, with values such as 0.00038 and 0.00052, signifying a high level of accuracy and minimal deviation. In contrast, the traditional method records higher error rates, including 0.00329 and 0.00134, suggesting less consistent performance and a greater margin for deviation. These results highlight the limitations of manual calibration, which is often subject to inconsistencies stemming from human error and procedural variability. The superior precision of the AI-driven system underscores its reliability, ultimately supporting improved meter quality and production efficiency.

Meanwhile, Table 3 compares various algorithmic configurations for Neutral IMAX (0.5 L) test point. Several XGBoost models were tested, incorporating tuning strategies like GridSearchCV, RandomizedSearchCV, and BayesSearchCV within pipeline structures. The proposed model, incorporating optimized parameters, emerged as most effective—achieving lowest RMSE of 0.005 and near-perfect accuracy scores (99.926% for training and 99.935% for testing). While its training time was relatively longer at 201.2 seconds, the prediction time remained rapid at 0.012 seconds, demonstrating both performance and efficiency.

3.3. Cost-effectiveness

Although the initial investment in the AI-based calibration system was higher than that of conventional methods, the long-term financial benefits were substantial. The system required an upfront cost of approximately $15,000, covering hardware integration, software deployment, and staff training. However, these expenses were offset by recurring savings in operational areas. Specifically, the reduction in manual labor from $500 to $200 per day, combined with fewer defects and less rework, generated average savings of $2,500 per production batch. The efficiency gains were equally significant. Processing time per meter was reduced from 20 to 10 minutes, while calibration accuracy improved from a 3.5% error rate to 0.8% in Table 4. These improvements reduced both labor intensity and material wastage, contributing to lower overall manufacturing costs. The return on investment (ROI) was calculated by comparing the net savings achieved within the first six months of deployment against the initial implementation cost. With cumulative savings of approximately $22,500 over this period, the system achieved an ROI of 150%. This result highlights not only the economic feasibility but also the practical value of integrating AI into the calibration process.

Table 3. Comparison of model performance on Neutral and IMAX (05L)

Test point	Model	RMSE	Accuracy (train)	Accuracy (test)	Train time (s)	Prediction time (s)
Neutral IMAX (05 L)	XGBoost GridSearchCV with Parameter	0.062	99.902	90.191	162.7	0.029
	XGBoost GridSearchCV with Pipeline	0.062	99.902	90.191	143.2	0.032
	XGBoost RandomizedSearchCV XGB_params with Pipeline	0.159	32.351	36.720	26.3	0.007
	XGBoost RandomizedSearchCV SVM_params with Pipeline	0.141	48.180	50.172	9.1	0.007
	XGBoost BayesSearchCV XGB_params with Pipeline	0.145	46.244	46.932	158.5	0.005
	XGBoost No Parameter	0.136	52.736	53.639	0.1	0.005
	Proposed model	0.005	99.926	99.935	201.2	0.012

Table 4. Comparison of cost-effectiveness between traditional and AI-driven calibration methods

Criteria	Traditional method	AI-implemented method	Improvement
Time (minutes per meter)	20 minutes	10 minutes	50% reduction
Calibration accuracy (RMSE)	3.5% error rate	0.8% error rate	77% improvement
Labor costs (per day)	$500	$200	60% reduction
Overall cost (per batch)	$5,000	$2,500	50% reduction
ROI	-	150% in 6 months	-

4. CONCLUSION

This study proposed an AI-driven calibration testing approach for electricity meter manufacturing, leveraging XGBoost with PSO-based hyperparameter tuning. The method demonstrated significant gains in predictive accuracy (lower RMSE), reduced testing time, and enhanced cost-efficiency compared to traditional manual calibration. A rigorous pipeline—incorporating data preprocessing, feature engineering, and systematic evaluation—proved essential in maximizing model performance. Experimental comparisons further underscored XGBoost's superiority. While LR and SVR exhibited limited capacity in handling the complex nonlinear patterns inherent in calibration data, RF performed better but still fell short in balancing accuracy with computational efficiency. By contrast, XGBoost with PSO consistently outperformed these alternatives, achieving both high accuracy and scalability. Beyond performance metrics, the approach yielded tangible economic benefits, including reduced labor costs, lower defect rates, and a rapid ROI, establishing its practical viability for large-scale deployment. Collectively, these findings highlight not only the technical effectiveness of the proposed solution but also its strategic value in advancing smart factory initiatives, offering manufacturers a robust and cost-effective pathway toward intelligent automation.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [R], upon reasonable request.

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