Energy Consumption Prediction and Anomaly Detection for Boiler Feed Pump in Power Plant Using Machine Learning and Deep Learning

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Received: Mar 02, 2025; **Revised:** Apr 19, 2025; **Accepted:** Apr 23, 2025

Abstract

Enhancing energy efficiency and operational reliability is crucial in power plant management, particularly for high-energy-consuming machines such as boiler feed water pumps (BFPs). These pumps play a vital role in the continuous generation of steam and electricity and must operate 24/7 to maintain power production stability. This study proposes the development of predictive models based on machine learning and deep learning techniques to accurately predict energy consumption and applies best models to detect anomalous behaviors in BFPs, enabling timely and preventive interventions. A dataset comprising 43,082 hourly records over five years, with 18 critical operational features, was analyzed using preprocessing and feature engineering techniques. Various predictive models were trained and evaluated, including Multiple Linear Regression, Regularized Regressions (Ridge, Lasso, ElasticNet), Support Vector Regression (SVR), Decision Tree, Ensemble Methods (Random Forest, XGBoost, CatBoost, LightGBM), and Deep Learning Architectures (DNN, RNN, GRU, LSTM). Among these models, SVR demonstrated the highest accuracy (MSE: 13.5573, R^2: 0.9838), followed closely by LightGBM. Feature importance analysis revealed that boiler feed pump discharge pressure and bearing housing vibration levels were the most influential variables in energy consumption prediction. Anomaly detection using the Interquartile Range (IQR) method classified deviations into two warning levels, enabling proactive maintenance strategies. Additionally, a Graphical User Interface (GUI) web application was developed for real-time monitoring, integrating predictive models, anomaly detection, and an automated email alert system to assist operators in responding to abnormal energy consumption events promptly. These results highlight the potential of predictive analytics and real-time monitoring in optimizing power plant operations, providing a foundation for extending predictive capabilities to other critical energy-intensive systems.

Keywords: Power Consumption Prediction, Boiler Feed Water Pumps, Machine Learning, Deep Learning, Anomaly Detection.

1. Introduction

The efficient operation and maintenance of power plants are essential for ensuring continuous and reliable electricity generation. Boiler feed water pump (BFPs) in **Figure 1** plays a critical role in supplying water to boilers for steam production and power generation process in **Figure 2** [1],[2]. Operating under high-pressure and high-temperature conditions, these pumps consume substantial energy, making efficiency optimization crucial. Inefficiencies or excessive energy use increase operational costs and may indicate mechanical degradation or suboptimal configurations. In the event of BFP failure or abnormal operation, the consequences can be severe—not only interrupting the steam supply for electricity generation but also affecting downstream processes such as industrial steam delivery to external customers. This may lead to production downtime, revenue loss, unmet customer demands, and missed sales opportunities, particularly in cogeneration plants where steam and electricity must be delivered concurrently under contractual obligations.

Figure 1 Boiler Feed Water Pump (BFP)

Accurate energy consumption prediction enhances BFP performance by enabling early anomaly detection, optimizing maintenance schedules, and reducing energy waste. Advanced machine learning (ML) and deep learning (DL) methodologies [3–5] leverage sensor data—including temperature, vibration, electrical power, and pressure differentials [6] to provide precise energy predictions. This predictive capability facilitates early inefficiency detection, cost reduction, and long-term sustainability in power plants.

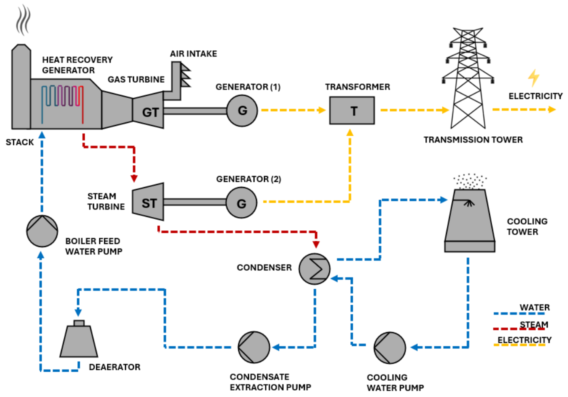

Figure 2 Power Plant Process

Numerous studies have explored ML-based energy consumption prediction in industrial settings, including power plants [3],[7]. These studies analyze historical operational data and key features such as pump speed, discharge pressure, flow rate, and ambient temperature to develop predictive models. Common ML techniques, including Support Vector Machines (SVM), Random Forest (RF), Decision Trees (DT), and XGBoost, each have distinct advantages and limitations [6]. For example, XGBoost excels in handling high-dimensional data and capturing complex relationships, achieving high accuracy in predictive tasks [8]. However, model effectiveness depends on dataset characteristics and power consumption patterns [4]. Further research is needed to identify the optimal ML approach for predicting BFP energy consumption across varying operational conditions.

In parallel, deep learning (DL) techniques, particularly deep learning sequential architecture such as Long Short-Term Memory (LSTM) networks, have proven to be powerful tools for time series forecasting [4]. LSTMs excel at processing sequential data and capturing temporal dependencies in power consumption patterns. Research has demonstrated their effectiveness in applications ranging from household appliances [7] to industrial facilities and large-scale power grid forecasting [4],[9]. However, DL models are computationally intensive and require substantial high-quality data for effective training [3]. Additionally, their "black box" nature poses interpretability challenges, making it difficult to understand the underlying predictive mechanisms.

Anomaly detection complements energy prediction by identifying unexpected deviations in operational data that may indicate inefficiencies or mechanical faults. The Interquartile Range (IQR) method effectively isolates outliers based on deviations from central tendencies. By categorizing anomalies by severity, IQR helps prioritize maintenance and mitigate operational risks [9]. When integrated with advanced ML and DL techniques, IQR-based anomaly detection strengthens predictive maintenance, enabling early fault detection and optimizing energy consumption.

Compared to previous studies, this study extends existing approaches by integrating anomaly detection into energy consumption prediction models and evaluating deployment feasibility in real-time environments. While earlier works have demonstrated the use of ML/DL for power consumption prediction, few have explicitly explored their integration with GUI-based interfaces and anomaly detection using statistical thresholds. This integration is crucial for improving real-world operational decision-making in power plants.

This study aims to develop ML and DL-based predictive models for forecasting energy consumption and detecting anomalies in BFPs. These insights enable early fault detection and proactive maintenance, enhancing operational efficiency, promoting energy conservation, and supporting sustainable energy generation.

2. Materials and Methods

To systematically develop and evaluate predictive models for energy consumption in boiler feed water pumps (BFPs), this study followed a structured workflow as illustrated in **Figure 3**. The methodology encompasses data collection, preparation, feature selection, model development, performance evaluation, and deployment feasibility. This integrated pipeline ensures consistency, interpretability, and robustness across each stage, supporting both offline analysis and deployment.

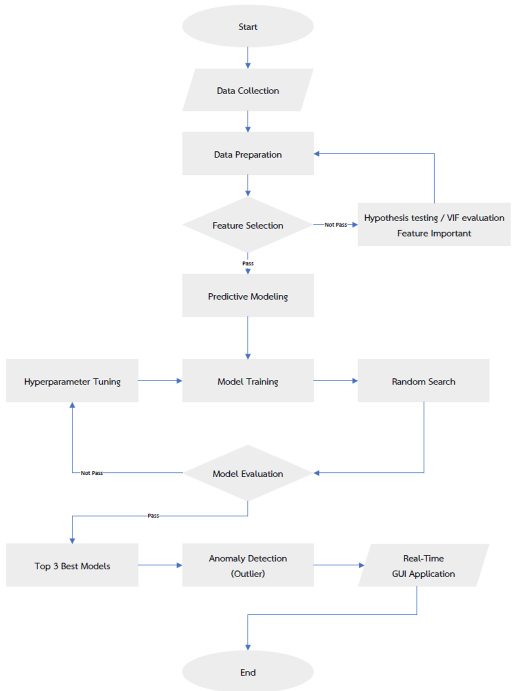

Figure 3 Methodological framework for BFP energy prediction.

2.1 Data Collection and Features

The dataset used in this study was collected from sensors installed in boiler feed water pump (BFP) systems in **Figure 4**, covering the period from January 1, 2020, to November 30, 2024. It comprises 43,082 hourly samples under varying operational conditions, featuring 18 critical attributes relevant to BFP operations, as shown in **Table 1**. These attributes were selected based on the expertise and practical recommendations of experienced plant operators, focusing on parameters that are known to affect energy consumption, mechanical integrity, and thermal performance. The selected attributes were categorized into three primary groups:

- Temperature parameters that reflect thermal load and potential overheating conditions.
- Vibration parameters that serve as indicators of mechanical balance, bearing wear, and potential misalignment.
- Energy performance parameters that directly influence and reflect energy consumption patterns.

Sensor data was acquired through the Plant Information System (PI System) in **Figure 5**, which continuously stores and archives real-time operational data from distributed sensors at fixed one-hour intervals. To retrieve the data, the PI Add-in for Microsoft Excel was used by querying specific sensor Tag/IDs. Excel was chosen for its seamless integration with the PI System and flexibility in tag-level customization, which facilitated efficient data extraction and initial validation. The dataset was then transferred to a Python-based environment via Google Colab for data preprocessing and model development

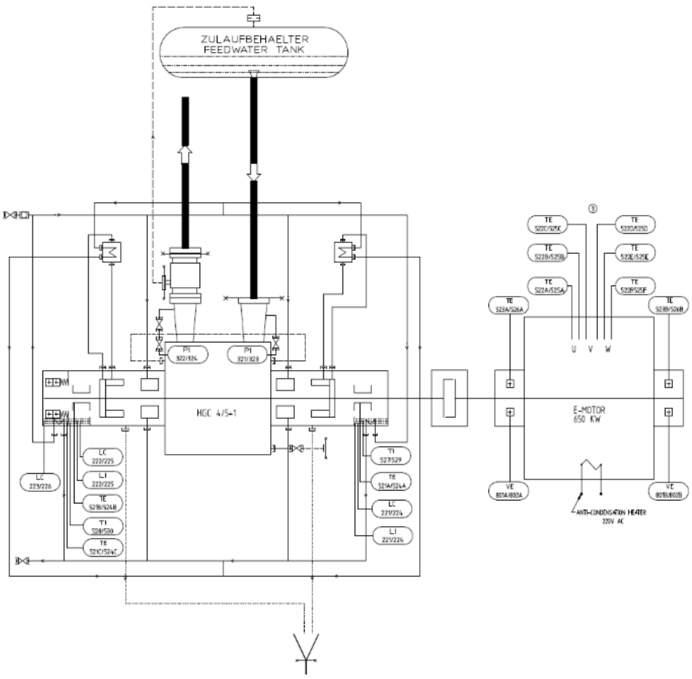

Figure 4 Piping and Instrumentation Diagram for BFPs sensors

Table 1 Key Operational Features and Sensor Data

BFPs Sensors	Critical Attributes
Temperature Parameters	1. Bearing temperatures Pump A–C 2. Bearing temperatures Motor A–B 3. Motor winding temperatures A–F
Vibration Parameters	1. Housing vibration levels A–B
Energy Performance Parameters	1. Pump discharge pressure 2. Power output of gas turbines Units 11–12 3. Active power consumption of the BFP (Target variable)

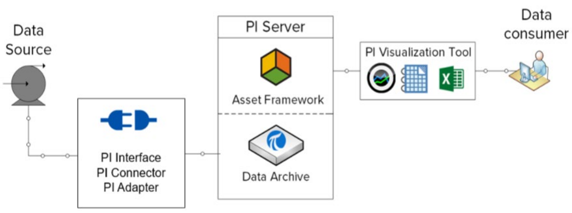

Figure 5 Plant Information System (PI System)

2.2 Data Preparation

To ensure dataset quality and optimize model performance, a structured data preparation pipeline was implemented. The process began with data cleaning, where duplicate records were removed, and outliers were handled using the Interquartile Range (IQR) method. Missing values were systematically addressed to maintain data completeness and consistency.

Feature engineering was performed to enhance predictive capabilities. Numerical variables were standardized using StandardScaler to normalize data ranges, ensuring uniformity across models. The dataset was split into training (80%) and testing (20%) subsets for model evaluation, with cross-validation techniques applied to improve robustness and prevent overfitting.

Exploratory data analysis (EDA) was performed to assess relationships among variables using descriptive statistics and correlation matrices in **Figure 6** each cell represents the correlation coefficient between pairs of variables, ranging from -1 (strong negative correlation) to +1 (strong positive correlation). Darker red shades indicate stronger positive correlations, while blue tones reflect stronger negative correlations.

The BFP#1_MOTOR_ACTIVE_POWER (target variable) shows to strong correlations with features such as BFW#1 _BEARING_HOUSING_VIBR_A and BFP#1_PUMP _DISCHARGE_PRESSURE indicating their potential predictive importance. Conversely, variables such as GTG12_POWER and BFW#1_PUMP_BEARING _TEMP#B show weak correlations, suggesting limited direct influence on the target variable. This heatmap supports the feature selection process by identifying redundant or highly collinear features (e.g., among winding temperatures A–F) and helps guide decisions in the subsequent modeling phase.

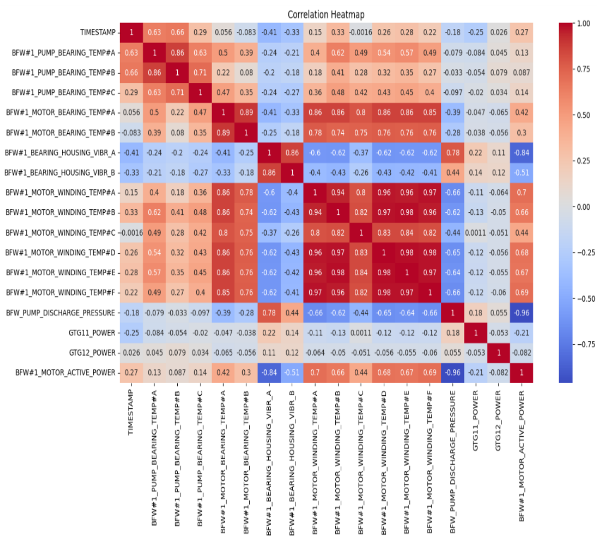

Figure 6 Correlation Heatmap of Operational Features for Boiler Feed Water Pump

2.3 Feature Selection for Model Development

The cleaned and preprocessed dataset is divided into two main parts: a training set and a test set. Both datasets undergo a feature selection process to identify the most important variables under different conditions. This study applies multiple importance analysis techniques, including Coefficient Analysis, Feature Importance from Tree-based Models, Permutation Importance to ensure that the selected variables significantly impact energy consumption.

To assess the influence of different variables on prediction accuracy, this study defines several feature selection conditions for model development, including:

1) Comprehensive Feature Utilization: Assesses model performance using all available data features to determine overall effectiveness.
2) Statistical Significance-Based Selection: Retains variables with p-values ≤ 0.05, ensuring only statistically significant predictors contribute to the target variable.
3) Multicollinearity: Filters out variables with a Variance Inflation Factor (VIF) > 10 to minimize high correlations among independent variables.
4) Feature Importance-Based Selection: Identifies the top 5 and top 10 most influential features based on their contribution to model performance.

2.4 Predictive Model

This study trained multiple ML and DL models using Python's Scikit-learn and TensorFlow libraries. The key models evaluated included in **Table 2**.

Table 2 Predictive Models for Energy Prediction

Machine Learning Model	1. Multiple Linear Regression
	2. Regularized Regressions
	3. Support Vector Regression
	4. Decision Trees Regression
	5. Random Forest Regression
	6. XGBoost Regression
	7. CatBoost Regression
	8. LightGBM Regression
Deep Learning Model	1. Deep Neural Networks (DNN)
	2. Recurrent Neural Networks (RNN)
	3. Gated Recurrent Units (GRU)
	4. Long Short-Term Memory (LSTM)

In addition, multiple linear regression (MLR) served as the baseline model due to its simplicity and interpretability. While effective, it is prone to overfitting in high-dimensional settings. To improve MLR, regularized techniques such as Ridge, Lasso, and ElasticNet were applied. These methods add penalty terms to prevent overfitting and enhance generalization. Hyperparameter tuning via Random Search optimized the regularization strength (alpha). Support vector regression can handle non-linear relationships by mapping data to higher-dimensional feature spaces.

Decision Trees Regression models the target variable by recursively splitting the data based on feature values. However, single decision trees can suffer from high variance, making them prone to overfitting. Random Forest addresses this by combining multiple trees to improve accuracy. XGBoost builds sequential trees to correct previous errors, offering high speed and accuracy. CatBoost efficiently handles categorical variables and reduces overfitting with ordered boosting. LightGBM accelerates training, reduces memory usage, and performs well with large datasets [10–11].

Building upon the Multilayer Perceptron architecture, Deep Neural Networks (DNNs) incorporate multiple hidden layers, significantly increasing the network's depth compared to the one or two hidden layers usually found in multilayer Perceptron architecture. Recurrent Neural Networks (RNN) excel at handling sequential data, but their performance can be hampered by challenges related to long-term dependencies, specifically the problems of vanishing and exploding gradients. The Long Short-Term Memory (LSTM) network offers a solution to these long-term dependency issues. There are three main gates in LSTM networks: input gate, output gate, and forget gate. This model effectively identifies dependent factors across multiple time scales and mitigates the vanishing gradient problem. Furthermore, the Gated Recurrent Unit (GRU) architecture simplifies the LSTM structure by eliminating a memory cell, leading to reduced computational requirements and accelerated training [12–13].

2.5 Hyperparameter Tuning

To achieve optimal model performance, this study implemented hyperparameter tuning for each model across different independent variable selection conditions. The tuning process employed Randomized Search in conjunction with K-fold Cross-Validation to identify the most suitable hyperparameters. This approach involved randomly selecting potential hyperparameter values within predefined ranges and evaluating their effectiveness using cross-validation.

The hyperparameter tuning process for each model is summarized in **Table 3** which outlines the models, their tuned hyperparameters, and the rationale behind the selected values.

Table 3 Hyperparameter Tuning

Model	Hyperparameters
Multiple Linear Regression	Default Parameters of LinearRegression()
Lasso, Ridge Regression	alpha
Elastic Net Regression	alpha, l1_ratio
Support Vector Regression	Kernel, C, epsilon
DecisionTrees Regression	max_depth, min_samples_split, min_samples_leaf
Random Forest Regression	n_estimators, max_depth
XGBoost, CatBoost, LightGBM Regression	n_estimators, learning_rate
Deep Learning Model	dense layers, learning_rate, activation function, optimizer, batch size, epochs

Each model was subjected to a hyperparameter tuning process designed to balance accuracy, complexity, and computational efficiency. The application of Randomized Search allowed for a broad yet computationally feasible exploration of parameter space, while K-fold Cross-Validation ensured robust evaluation of model performance across varying data partitions.

2.6 Evaluation Metrics

The performance of predictive models was assessed using Mean Squared Error (MSE) and coefficient of determination (R^2) to measure the prediction effectiveness. The formulas are:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \quad (1)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)}{\sum_{i=1}^{N}(y_i - \bar{y}_i)} \quad (2)$$

Eqs. (1)–(2) refer to a set of N represents the total number of samples, $\hat{y}_i$ represents the predicted values, and $\bar{y}_i$ is the meaning of the actual values. These metrics evaluate model accuracy and explanatory power, ensuring the effectiveness of predictive modeling for BFPs operations.

2.7 Outlier Detection

Outlier detection is a crucial step in assessing anomaly detection for boiler feed water pumps. This process uses residuals (the difference between predicted and actual values) to identify anomalies via the IQR method. The IQR was calculated as Q3 – Q1, with anomaly thresholds defined as:

$$LowerBound_{res} = Q1_{res} - (1.5 \times IQR_{res}) \quad (3)$$

$$UpperBound_{res} = Q3_{res} + (1.5 \times IQR_{res}) \quad (4)$$

For more severe anomalies:

$$LowerBound_{res} = Q1_{res} - (3 \times IQR_{res}) \quad (5)$$

$$UpperBound_{res} = Q3_{res} + (3 \times IQR_{res}) \quad (6)$$

This approach Eqs. (3)–(6) differs from conventional anomaly classification methods, such as supervised classification, by not requiring pre-labeled anomaly data, which is often unavailable in real-world settings. The IQR-based thresholding allows the model to remain adaptable and interpretable, aiding in early fault detection even without prior failure events in the dataset.

2.8 Feasibility in Real-Time GUI Applications

To facilitate real-time energy consumption prediction for boiler feed water pumps (BFPs), this study developed a web-based application utilizing Streamlit Platform on a local server. The selection of models for deployment ML and DL models in real-time applications depends on balancing prediction accuracy and computational efficiency, ensuring seamless real-time processing of streaming sensor data on the PI system.

The computational cost varies significantly based on the complexity of the models and the algorithms used. For practical deployment, models were categorized into 3 groups:

1) Simple Models (Low Cost):
   - Multiple Linear Regression
   - Regularized Regression (Ridge, Lasso, ElasticNet)
2) Intermediate Models (Moderate Cost):
   - Support Vector Regression
   - Decision Trees Regression
   - Ensemble Methods (Random Forest, XGBoost, CatBoost, LightGBM)
3) Complex Models (High Cost):
   - Deep Neural Networks
   - Recurrent Neural Networks (RNN)
   - Long Short-Term Memory (LSTM)
   - Gated Recurrent Units (GRU)

This categorization aids in selecting appropriate models tailored to the operational constraints of the local server environment.

3. Results and Discussion

The performance of the predictive models was evaluated using Mean Squared Error (MSE) and the coefficient of determination (R^2) across three feature selection strategies: all features, top 10 features, and top 5 features. The results are summarized in **Table 4** and illustrated in **Figure 7**. In the figure, the horizontal bars (in blue) represent the MSE values, while the red line indicates the corresponding R^2 scores. The visualization clearly highlights the performance differences among the models under each feature selection condition.

3.1 Model Performance

Among all models, Support Vector Regression (SVR) demonstrated the highest predictive accuracy, with an MSE of 13.5573 and an R^2 of 0.9838 using all available features. This confirms SVR's effectiveness in capturing complex, non-linear relationships between variables. LightGBM also performed remarkably well, achieving an MSE of 14.1922 and an R^2 of 0.9831, and consistently ranking among the top-performing models.

When reducing the input to the top 10 most important features, both SVR and LightGBM maintained nearly the same level of accuracy. SVR recorded an MSE of 14.2818 and an R^2 of 0.9830, while LightGBM achieved an MSE of 14.1443 and an R^2 of 0.9831. This indicates that most of the predictive power is concentrated in a relatively small subset of features.

However, further reduction to the top 5 features resulted in a noticeable decline in model performance. SVR's MSE increased to 20.8288 (R^2: 0.9751), and similar declines were observed in other models, suggesting that broader feature inclusion is necessary to capture the full variability of energy consumption behavior in BFPs.

Ensemble models such as XGBoost and CatBoost also achieved strong results, with XGBoost yielding an MSE of 15.1769 and CatBoost 15.1286 using all features. Although slightly less accurate than SVR and LightGBM, they remained competitive across all feature configurations.

Regularized regression models (Lasso, Ridge, and ElasticNet) produced results similar to Multiple Linear Regression (MLR), but struggled with non-linear relationships, limiting their overall performance. Meanwhile, deep learning models, including GRU (MSE: 15.6378, R^2: 0.9813) and LSTM (MSE: 17.8306, R^2: 0.9787), demonstrated good accuracy and alignment with observed consumption patterns.

In summary, SVR and LightGBM consistently outperformed other models in terms of predictive accuracy, particularly when all or the top 10 features were used. These findings support their use as reliable predictive tools for monitoring and managing energy consumption in boiler feed water pumps.

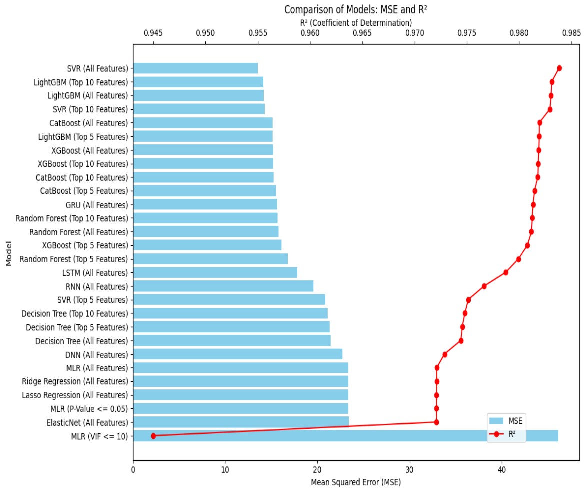

Figure 7 Model Performance of All Strategies

3.2 Feature Important

The analysis of feature importance various models identified BFW_PUMP_DISCHARGE_PRESSURE as the most influential variable. This feature directly reflects the hydraulic load imposed on the pump, which is closely linked to the energy required for water circulation within the steam generation process. Its high predictive contribution across all model types underscores its central role in energy consumption dynamics.

In addition, bearing housing vibration levels (BFW#1_BEARING_HOUSING_VIBR_A and BFW#1_BEARING_HOUSING_VIBR_B) emerged as critical indicators in several model families, including kernel-based regressors, tree-based models, and ensemble methods. Elevated vibration may indicate mechanical imbalance, wear, or misalignment—factors that can increase friction and reduce pump efficiency, thereby increasing energy usage. Their consistently high ranking across modeling techniques further validates their relevance as condition-monitoring variables.

Conversely, temperature variables were among the least influential features. This finding suggests that, within the normal operational temperature range, variations in temperature do not significantly affect energy consumption. This trend was consistently observed across all models, reinforcing their limited predictive value in the context of BFP energy modeling.

These results support the conclusion that features directly associated with mechanical health are more impactful for predicting energy usage than those related to internal electrical temperature conditions.

Table 4 Performance Metrics for Predictive Mode

Model Group	Predictive Model	Feature Selection	Performance Metrics (Test Dataset)	
			MSE	R^2
Linear Regression Models	Multiple Linear Regression (MLR)	All features	23.3543	0.9721
		Features with both p-values ≤ 0.05 and VIF ≤ 10.	36.4519	0.9565
Linear Regression with Regularization	Lasso Regression	All features	23.3730	0.9721
	Ridge Regression	All features	23.3543	0.9721
	ElasticNet Regression	All features	23.3810	0.9721
Kernel-Based Regression Model	Support Vector Regression (SVR)	All features	13.5573	0.9838
		Top 5 most features	20.8288	0.9751
		Top 10 most important features	14.2818	0.9830
Tree-Based Regression Models	Decision Tree Regression	All features	21.4189	0.9744
		Top 5 most important features	21.3150	0.9746
		Top 10 most important features	21.0988	0.9748
Ensemble Method	Random Forest Regression	All features	15.7650	0.9812
		Top 5 most important features	16.7989	0.9800
		Top 10 most important features	15.7012	0.9813
	XGBoost Regression	All features	15.1769	0.9819
		Top 5 most important features	16.0858	0.9808
		Top 10 most important features	15.2126	0.9818
	CatBoost Regression	All features	15.1286	0.9819
		Top 5 most important features	15.5188	0.9815
		Top 10 most important features	15.2559	0.9818
	LightGBM Regression	All features	14.1922	0.9831
		Top 5 most important features	15.1394	0.9819
		Top 10 most important features	14.1443	0.9831
Neural Network Models	Deep Neural Network (DNN)	All features	22.7365	0.9729
	Recurrent Neural Network (RNN)	All features	19.5486	0.9767
	Gated Recurrent Unit (GRU)	All features	15.6378	0.9813
	Long Short-Term Memory (LSTM)	All features	17.8306	0.9787

3.3 Anomaly Detection

Energy consumption anomalies were identified using the IQR method, with anomaly thresholds set at 1.5 and 3 to define the lower and upper bounds. These thresholds categorized anomalies into two severity levels. For the three top-performing models, the anomaly detection boundaries were calculated separately as follows:

1) SVR (All features):
   Warning Level 1 (-7.5079, +7.6733)
   Warning Level 2 (-13.2008, +13.3662)
2) LightGBM (Top 10 features):
   Warning Level 1 (-7.5156, +7.5226)
   Warning Level 2 (-13.1550, +13.1620)
3) LightGBM (All features):
   Warning Level 1 (-7.4368, +7.4404)
   Warning Level 2 (-13.0158, +13.0193)

A confirmed anomaly was defined only when all three models simultaneously detected a deviation at the same severity level. The final detection identified 183 Warning Level 1 events and 5 Warning Level 2 events between January 2020 and November 2024 in **Figure 8** illustrates the predictions from the three top-performing models—SVR (All Features) in green line, LightGBM (Top 10 Features) in yellow line, and LightGBM (All Features) in purple line—over the full evaluation period. The chart shows actual power consumption alongside predicted values, with orange and red markers denoting Level 1 and Level 2 anomalies, respectively. Notably, anomaly points are highlighted only when all three models simultaneously detect deviations beyond defined thresholds. This consensus-based strategy enhances anomaly detection robustness, reducing false positives and reinforcing the system's reliability. The time series visualization also demonstrates how well the predictive models align with actual energy patterns, capturing both regular trends and deviations.

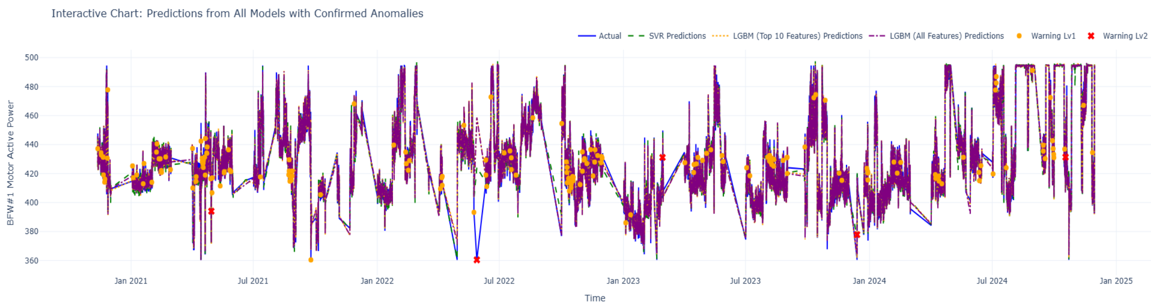

Figure 8 Time series plot comparing actual power consumption with predictions from SVR and LightGBM model

3.4 GUI Development and Notification System

To support the practical implementation of the developed predictive models and anomaly detection system, a web-based graphical user interface (GUI) was developed, as shown in **Figure 9**. This interactive dashboard enables real-time monitoring of boiler feed water pump (BFP) energy consumption and enhances operational decision-making.

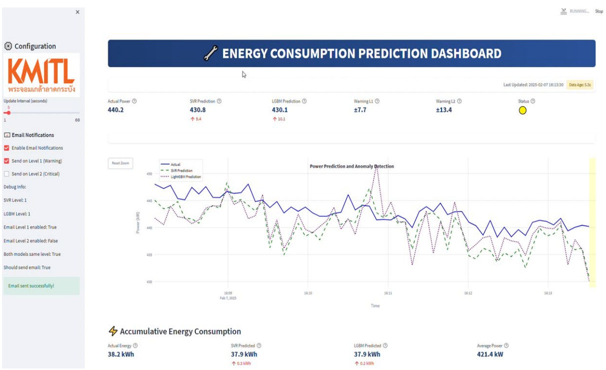

Figure 9 GUI interactive Web Application

The GUI integrates predictive models—specifically SVR and LightGBM—and displays real-time comparisons between actual and predicted power consumption. It also overlays anomaly detection results based on predefined IQR thresholds, with Warning Level 1 and Level 2 clearly marked on the time-series graph for intuitive visualization.

Key features of the system include:

1) Real-time Monitoring: The GUI visualizes actual power consumption versus predicted values.
2) Anomaly Detection: The system identifies and highlight anomalies periods using selected model based on predefined warning level.
3) Email Notification System: When an anomaly is detected, an automated email alert is sent to the operators with relevant details and CSV logs.
4) Customizable Settings: Operators can configure the update interval for prediction and visualization between 1 to 60 seconds, enable or disable email notifications for different warning levels.

The integration of this GUI and automated alert system significantly improves operational awareness and energy management efficiency by reducing response time to unexpected anomalies, enabling operators to take swift corrective actions. It minimizes operational risks by facilitating proactive intervention, ensuring that energy anomalies are addressed before they escalate. Additionally, it enhances predictive maintenance planning, which helps reduce equipment downtime, optimize energy usage, and extend the operational life of critical machinery.

4. Conclusion

This study developed and evaluated predictive models for energy consumption and applied best models for anomaly detection in boiler feed water pumps (BFPs) using machine learning (ML) and deep learning (DL) techniques. The results demonstrate that Support Vector Regression (SVR) with all features and LightGBM with both all-feature and top-10 feature selections achieved the highest prediction accuracy. Feature importance analysis identified boiler feed pump discharge pressure and bearing housing vibration levels as the most influential factors affecting energy consumption, providing critical insights for predictive maintenance.

Anomalies were detected using the Interquartile Range (IQR) method applied to model residuals, with thresholds categorized into two severity levels. A consensus-based strategy was employed, where anomalies were confirmed only when all top-performing models agreed. This method yielded 183 Level 1 and 5 Level 2 anomaly events, demonstrating the framework's potential in early identification of inefficiencies and mechanical issues.

To enable real-time application, a graphical user interface (GUI) web application was developed. The system integrates energy prediction, anomaly visualization, and automated email notifications, allowing plant operators to monitor performance continuously and respond promptly to abnormal conditions before inefficiencies escalate into significant energy losses or unplanned outages. This supports improved maintenance planning, reduced energy waste, and enhanced operational efficiency.

While the framework shows promising results, it was developed without access to historical failure records, limiting validation of anomaly detection against actual fault events. Future deployments should include mechanisms for field verification, such as coordinated feedback from operators and maintenance logs, to support ongoing model retraining and accuracy improvement. Establishing operational policies for real-time monitoring and human-in-the-loop validation will further strengthen the reliability of the predictive system and allow scalable extension to other critical equipment within power plant operations.

5. Acknowledgments

I sincerely thank Global Power Synergy Company (GPSC) for providing crucial knowledge and data, making this research possible.

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