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INTERPRETABLE MACHINE LEARNING FOR GEOTHERMAL POWER GENERATION PREDICTION: AN XGBOOST–SHAP APPROACH

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ABSTRACT

Geothermal power plants require accurate forecasting models to maintain operational stability and improve energy efficiency. However, electricity generation is influenced by complex thermodynamic and chemical parameters that are difficult to model using conventional approaches. Therefore, this study proposes an explainable machine learning framework based on Extreme Gradient Boosting (XGB) and SHapley Additive exPlanations (SHAP) for electricity generation prediction using geothermal operational data. The dataset consisted of 14,252 hourly operational records collected from March 2022 to December 2024. Model performance was evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and coefficient of determination (R^2), while SHAP was employed to analyze feature contributions and improve model interpretability. Experimental results showed that the XGB model achieved an MAE of 0.26009 MW, an RMSE of 0.47537 MW, and an R^2 of 0.99499. SHAP analysis revealed that steam flow rate and pressure-related variables were the most influential factors affecting electricity generation prediction. These findings demonstrate that the proposed XGB-SHAP framework can provide both accurate prediction performance and interpretable insights for geothermal power plant operation and performance monitoring.

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1. INTRODUCTION

Geothermal energy plays an important role in sustainable electricity generation because it provides stable power production with lower carbon emissions compared to conventional fossil fuel power plants [1]. Accurate electricity generation prediction is required to maintain operational stability, optimize energy management, and support efficient geothermal power plant operation. The availability of reliable operational monitoring systems is also essential to support data-driven analysis and predictive modeling in power generation environments. Previous studies have demonstrated the implementation of IoT-based electrical monitoring systems for recording and managing power-related operational data [2]. Forecasting errors may lead to inefficient resource utilization, suboptimal operational planning, and reduced generation reliability. In addition, inaccurate prediction of electricity output can affect power scheduling and grid management, particularly as renewable energy sources become increasingly integrated into modern power systems. Therefore, reliable forecasting methods are essential to support operational decision-making and improve the overall efficiency of geothermal power plant management. However, electricity generation in geothermal systems is influenced by complex operational parameters such as steam flow, pressure, temperature, and chemical characteristics, which create nonlinear relationships that are difficult to model using conventional analytical approaches.

Recently, machine learning methods have been widely applied in prediction and forecasting problems because of their capability to model complex nonlinear relationships more effectively than conventional analytical approaches. In the geothermal domain, various machine learning algorithms, including XGBoost, Random Forest, Support Vector Regression (SVR), K-Nearest Neighbors (KNN), Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), Deep Neural Networks (DNN), and Multilayer Perceptrons (MLP), have been employed for geothermal electricity generation forecasting, geothermal resource assessment, and geothermal system performance prediction [3], [4]. These studies demonstrated that machine learning approaches can effectively capture the nonlinear behavior of geothermal systems and provide reliable prediction performance.

Among the available machine learning methods, Extreme Gradient Boosting (XGB) has attracted considerable attention due to its strong predictive capability, regularization mechanism, and computational efficiency [5]. Previous studies have reported that XGB achieves high prediction accuracy in various energy forecasting applications. However, despite its predictive performance, XGB is often regarded as a black-box model because the contribution of individual input variables to prediction outcomes cannot be directly interpreted [6]. This limitation may reduce user trust and hinder the practical adoption of machine learning models in operational decision-making processes, particularly in critical energy systems such as geothermal power plants.

To improve model interpretability, Explainable Artificial Intelligence (XAI) methods are increasingly utilized in machine learning studies [7]. One of the most widely used XAI approaches is SHapley Additive exPlanations (SHAP), which provides both global and local interpretations by quantifying feature contributions toward prediction outputs. Although previous studies have successfully applied machine learning algorithms for geothermal electricity generation forecasting, most existing research primarily focuses on predictive accuracy and provides limited insight into how operational variables influence model predictions [4], [6]. As a result, the decision-making process of many forecasting models remains difficult to interpret, reducing transparency and practical applicability in geothermal power plant operations. Furthermore, while XGB-SHAP frameworks have been applied in various energy forecasting domains, their application to geothermal electricity generation forecasting using real operational geothermal power plant data remains limited. Therefore, a scientific gap exists in the development of forecasting models that simultaneously provide high predictive performance and interpretable explanations of the operational factors affecting geothermal electricity generation. To address this gap, this study proposes an explainable machine learning framework that integrates Extreme Gradient Boosting (XGB) with SHAP for electricity generation prediction in geothermal power plants. Unlike previous studies that primarily emphasized prediction accuracy, the proposed framework combines predictive modeling with explainability analysis to identify and quantify the contribution of operational parameters to prediction outcomes. The main contributions of this study are: (1) the development of an XGB-based prediction model using real geothermal operational data, (2) the application of SHAP to provide both global and local explanations of model predictions, and (3) the generation of interpretable insights that may support a better understanding of the operational factors influencing electricity generation. To the best of our knowledge, few studies have combined XGB-based prediction and SHAP-based explainability using multi-year real operational geothermal power plant data for electricity generation forecasting. Furthermore, this study seeks to answer the following research question: Can an XGB-SHAP framework provide accurate and interpretable electricity generation predictions for geothermal power plant operations?

2. RESEARCH METHOD

This section describes the methodology used in this study for electricity generation prediction in geothermal power plants. The proposed framework consisted of data collection, preprocessing, XGB model development, SHAP-based explainability analysis, and model evaluation. A quantitative computational approach was employed to model the nonlinear relationships between geothermal operational parameters and electricity generation output. The overall research workflow is presented systematically to ensure reproducibility and reliability of the proposed prediction framework [8], [9]. Figure 1 illustrates the overall research workflow adopted in this study.

The process began with data collection and variable identification, followed by data preprocessing to improve data quality and prepare the dataset for model development. During preprocessing, duplicate records and invalid observations were assessed through data validation procedures. Missing values in numerical variables were handled using median imputation, while categorical variables were processed using one-hot encoding. Furthermore, the Flow-to-Load Ratio variable was excluded from the modeling process because it is mathematically derived from electrical load and may introduce information leakage. No additional outlier removal procedure was applied because the operational values were verified against plant monitoring records and considered representative of actual operating conditions.

Subsequently, the XGB model was developed and optimized through hyperparameter tuning using RandomizedSearchCV combined with TimeSeriesSplit cross-validation. The hyperparameter optimization process explored multiple parameter combinations to identify the most suitable model configuration. The search space used in RandomizedSearchCV is presented in Table 1. The search space included n_estimators, learning_rate, max_depth, subsample, colsample_bytree, min_child_weight, gamma, reg_alpha, and reg_lambda. The optimal hyperparameter combination was selected based on the lowest cross-validation error obtained during the tuning process.

Table 1: Hyperparameter Search Space Used in RandomizedSearchCV

Hyperparameter	**Search Space**
`n_estimators`	100, 200, 300, 500
`learning_rate`	0.01, 0.05, 0.10
`max_depth`	3, 4, 5, 6, 8
`subsample`	0.6, 0.8, 1.0
`colsample_bytree`	0.6, 0.8, 1.0
`min_child_weight`	1, 3, 5
`gamma`	0, 0.01, 0.1
`reg_alpha`	0, 0.01, 0.1
`reg_lambda`	1, 5, 10

The optimal hyperparameter combination obtained from the tuning process is presented in Table 3. The trained model was then evaluated using regression performance metrics, while SHAP was employed to provide both global and local explanations of the prediction results.

2.1. Research Design

This study employed a quantitative computational approach using supervised machine learning techniques to predict electricity generation in geothermal power plants. The research focused on developing an XGB regression model and interpreting its predictions using SHAP [10]. The computational approach was selected because it is capable of modeling complex nonlinear relationships between geothermal operational parameters and electricity generation output. In addition, XAI techniques were incorporated to improve model transparency and interpretability through feature contribution analysis [8], [9], [11].

2.2. Data Source And Variables

The dataset used in this study was obtained from geothermal power plant operational records collected from March 2022 to December 2024. The dataset reflects actual plant operating conditions and consists of 14,252 observations recorded at an hourly sampling interval. Therefore, the data frequency used in this study was hourly, allowing the model to capture temporal variations in geothermal operational conditions and electricity generation output. The dataset comprised operational parameters related to geothermal electricity generation, including steam mass flow rate (t/h), gauge pressure (bar(g)), absolute pressure (bar(a)), temperature (°C), fluid acidity level (pH), electrical conductivity (EC), chloride concentration (Cl^-), and total dissolved solids (TDS). Turbine load (MW) was defined as the target variable for prediction. Before analysis, the dataset was inspected to ensure data consistency and completeness. Table 2 presents the variables used in this study. A data quality assessment was performed before model development. Duplicate records, invalid observations, and missing values were examined through consistency checking and data validation procedures. No duplicate records or invalid observations were identified during the data quality assessment. Missing values were handled using median imputation for the corresponding numerical variables. As a result, the final dataset used for model development consisted of 14,252 valid hourly observations.

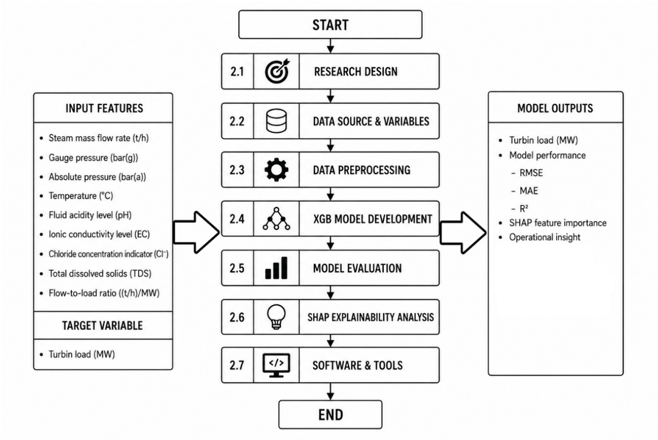

Figure 1. Workflow Diagram

Table 2: Operational Variables Used in This Study

Variable	Unit	Description	Category
Load	MW	Electrical power output	Target
Flow Rate	t/h	Steam mass flow rate	Input
Flow-to-Load Ratio	(t/h)/MW	Flow efficiency indicator (Flow Rate:Load)	Derived
Gauge Pressure	bar(g)	Relative steam pressure	Input
Absolute Pressure	bar(a)	Total steam pressure	Input
Temperature	°C	Steam inlet temperature	Input
pH	–	Fluid acidity level	Input
EC	μS/cm	Ionic conductivity level	Input
Cl^-	mg/L	Chloride concentration indicator	Input
TDS	mg/L	Total Dissolved Solids	Input

Although the Flow-to-Load Ratio was available in the original dataset, it was excluded from the modeling process because it is mathematically derived from both steam flow rate and electrical load, making it unsuitable for predictive modeling due to its direct dependency on the target variable and its potential to introduce information leakage. In addition, only operational parameters that would be available at the time of prediction were retained as input features. After preprocessing and data validation, 14,252 valid observations were retained for analysis and subsequently divided using a chronological 80:20 train-test split strategy, where earlier observations were used for training and later observations were reserved for testing.

2.3. Data Preprocessing

Before model development, the dataset underwent several preprocessing stages to improve data quality and model reliability. Missing values were handled using median imputation, while duplicate and invalid records were assessed through data validation procedures. The timestamp attribute was converted into datetime format to preserve the temporal characteristics of the operational data. Additional temporal features were generated from the timestamp variable, including hour, day of week, and month. These features were incorporated to capture temporal operational patterns that may influence electricity generation. To prevent information leakage during model training, several non-predictive and leakage-prone variables were excluded from the feature set. A time-based data partitioning strategy was applied, where 80% of the earlier data were used for training and the remaining 20% of future data were used for testing. This approach was selected to preserve temporal dependencies and simulate real-world forecasting conditions, which are commonly adopted in time-series prediction studies [12].

2.4. XGB Model Development

The prediction model in this study was developed using XGB, which is an ensemble learning algorithm based on gradient boosting decision trees [13]. XGB improves prediction performance by sequentially constructing decision trees to minimize prediction errors through gradient optimization [5]. XGB was selected because of its ability to model nonlinear relationships, incorporate regularization mechanisms, and achieve high predictive accuracy with relatively efficient computational cost. The prediction model can be expressed as:

$$\hat{y}_i = \sum_{k=1}^{K} f_k(x_i), f_k \in \mathcal{F} \tag{1}$$

where $\hat{y}_i$ represents the predicted output, f_k denotes the decision trees, and F represents the functional space of regression trees [14]. The objective function of XGB is defined as:

$$Obj = \sum_{i=1}^{K} l\left(y_i, \hat{y}_i\right) + \sum_{k=1}^{K} \Omega(f_k) \tag{2}$$

where l denotes the loss function and $\Omega(f_k)$ represents the regularization term used to control model complexity and reduce overfitting. Hyperparameter optimization was performed using Randomized Search CV combined with Time Series Split cross-validation [13]. Time Series Split was employed to preserve the chronological order of the observations during model validation and to minimize information leakage from future observations. Several hyper parameters were optimized, including the number of estimators, learning rate, maximum tree depth, sub sampling ratio, and column sampling ratio. The optimal hyperparameter configuration obtained from the Randomized Search CV procedure is presented in Table 3. These parameters were selected based on the lowest cross-validation RMSE and were subsequently used for model training and evaluation. The tuning process was conducted exclusively on the training dataset to avoid data leakage. Furthermore, all experiments were performed using a fixed random seed (random_state = 42) to ensure reproducibility and consistency of the experimental results.

Table 3: Optimal Hyperparameters Obtained from RandomizedSearchCV

Hyperparameter	**Optimal Value**
`n_estimators`	200
`learning_rate`	0.05
`max_depth`	6
`subsample`	0.60
`colsample_bytree`	0.80
`min_child_weight`	5
`gamma`	0.01
`reg_alpha`	0.01
`reg_lambda`	5

2.5. Model Evaluation

Model performance was evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and coefficient of determination (R^2). These evaluation metrics were selected because they are widely used in regression-based prediction studies. The mathematical formulations of the evaluation metrics are defined as:

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |y_i - \hat{y}_i| \tag{3}$$

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

$$R^2 = 1 - \frac{\sum_{i=1}^{n} \left(y_i - \hat{y}_i\right)^2}{\sum_{i=1}^{n} \left(y_i - \bar{y}\right)^2} \tag{5}$$

Lower MAE and RMSE values indicate better prediction accuracy, while higher R^2 values indicate stronger agreement between actual and predicted electricity generation outputs [12], [15].

2.6. SHAP-Based Explainability Analysis

To improve model interpretability, SHapley Additive exPlanations (SHAP) were utilized to analyze the contribution of each feature toward prediction results [16]. SHAP is an Explainable Artificial Intelligence (XAI) method based on cooperative game theory that calculates Shapley values to quantify feature importance. The SHAP value calculation is expressed as:

$$\phi_i = \sum_{S \subseteq N \setminus i} \frac{|S|!(|N| - |S| - 1)!}{|N|} [f(S \cup i) - f(S)] \tag{6}$$

where ϕ_i represents the contribution of feature i, and $f(S)$ denotes the prediction generated from subset S of features. In this study, SHAP summary plots were used to identify globally influential features, while local SHAP explanations were utilized to analyze feature contributions for individual prediction instances [17], [18]. Global explanations were obtained using SHAP summary plots to identify the overall influence of each feature, whereas local explanations were generated to analyze feature contributions for individual prediction instances. This approach enabled better understanding of how operational parameters affected electricity generation prediction.

2.7. Software Tools

All experiments were conducted using Python 3 in the Google Colaboratory environment. Pandas and NumPy were used for data preprocessing, Scikit-learn for model evaluation and hyperparameter optimization, XGBoost for regression modeling, SHAP for explainability analysis, and Matplotlib and Seaborn for data visualization.

3. RESULTS AND ANALYSIS

This section presents the experimental results and analysis of the proposed XGB-SHAP framework for electricity generation prediction in geothermal power plants. The discussion begins with an overview of the dataset characteristics, followed by the evaluation of prediction performance using MAE, RMSE, and R^2 metrics. Subsequently, the predictive behavior of the model is analyzed through actual-versus-predicted comparisons and residual analysis. Finally, SHAP-based explainability analysis is conducted to investigate the contribution of individual operational parameters and to provide interpretable insights into the prediction mechanism of the developed model.

3.1. Dataset Characteristic

The dataset used in this study consisted of geothermal power plant operational records collected from March 2022 to December 2024. The dataset contained thermodynamic and chemical parameters associated with electricity generation performance, including steam flow rate, pressure-related variables, temperature, pH, electrical conductivity, chloride concentration, and total dissolved solids. Prior to model development, descriptive statistical analysis was conducted to provide an overview of the characteristics and distribution of the variables used in the study.

Table 4: Descriptive Statistics of Operational Variables

Parameter	**Mean**	**Std**	**Min**	**25%**	**50%**	**75%**	**Max**
Load	46.604	6.858	25.590	44.560	48.640	51.110	57.640
Flow Rate	323.753	34.257	229.650	309.968	325.300	341.420	403.770
Gauge Pressure	8.441	0.301	7.730	8.220	8.420	8.630	10.050
Absolute Pressure	0.173	0.130	0.010	0.080	0.160	0.250	1.060
Temperature	176.003	1.171	171.720	175.170	175.840	176.650	179.710
pH	5.557	0.263	4.730	5.380	5.550	5.700	7.080
EC	460.230	36.242	225.000	455.000	463.000	472.000	680.000
Cl^-	1.007	0.154	0.340	0.910	1.020	1.110	1.490
TDS	75.596	123.488	1.000	20.000	47.000	89.000	1280.000

Table 4 presents the descriptive statistics of the operational variables used in this study. The electricity generation output exhibited variability throughout the observation period, reflecting changes in geothermal operating conditions and steam availability. The steam flow rate showed substantial variation compared to other variables, indicating its potential influence on electricity generation performance. Pressure-related variables and temperature also demonstrated notable fluctuations, suggesting their importance in describing turbine inlet operating conditions. Meanwhile, chemical parameters such as pH, electrical conductivity, chloride concentration, and total dissolved solids provided additional information regarding fluid characteristics that may indirectly affect geothermal system performance. Overall, the dataset exhibited sufficient variability and data coverage to support the development of a machine learning-based prediction model and explainability analysis.

Figure 2 presents the Pearson correlation matrix of the operational variables used in this study. The analysis was conducted to investigate the relationships among predictor variables and the target variable, as well as to provide

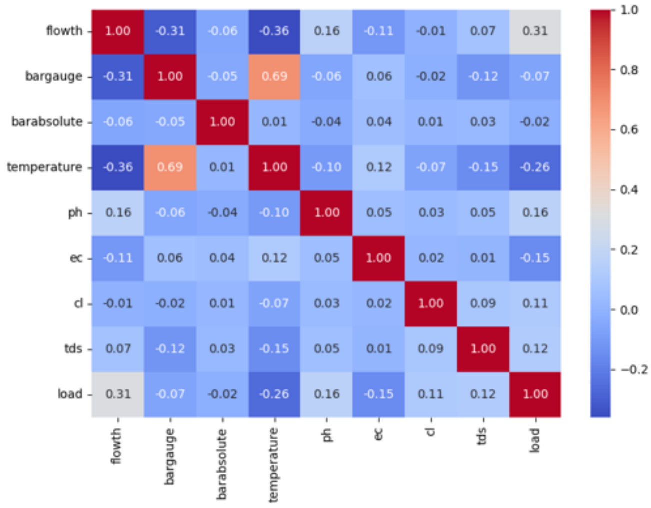

Figure 2. Correlation Matrix of Operational Variables

additional evidence regarding potential information leakage. The results indicate that no predictor exhibited a perfect or near-perfect correlation with electricity generation output. Furthermore, the Flow-to-Load Ratio variable, which was directly derived from electrical load, was excluded during preprocessing to prevent information leakage. These findings suggest that severe information leakage was unlikely in the final dataset used for model development and evaluation. In addition, chronological train-test splitting and TimeSeriesSplit cross-validation were employed throughout model development and validation to minimize the possibility of information leakage from future observations into the training process.

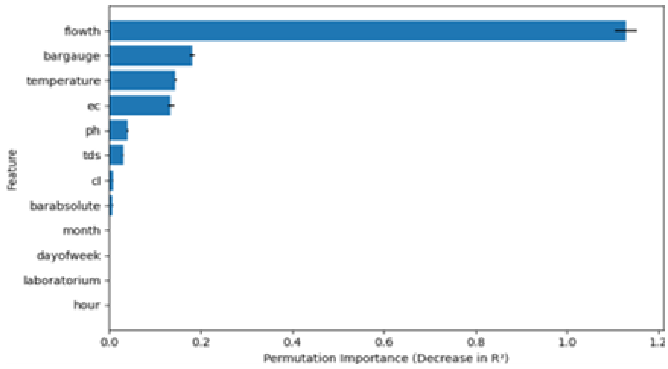

Figure 3. Permutation Importance of Operational Variables

Figure 3 presents the permutation importance analysis of the XGB model. The analysis was conducted by measuring the decrease in the coefficient of determination (R^2) after randomly permuting each feature. The results indicate that steam flow rate (flowth) was the most influential predictor of electricity generation, followed by pressure-related variables (bargauge and barabsolute) and temperature. In contrast, temporal variables such as month, dayofweek, and hour, as well as the laboratory category, exhibited negligible contributions to model performance. These findings suggest that electricity generation prediction was primarily driven by operational and thermodynamic parameters rather than calendar-related factors. Furthermore, the permutation importance results are consistent with the SHAP analysis, providing additional evidence regarding the reliability and interpretability of the proposed prediction framework.

3.2. XGB Prediction Performance

The predictive performance of the proposed XGB model was evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and coefficient of determination (R^2). These evaluation metrics were selected because they are widely used to assess prediction accuracy and model generalization capability in regression-based machine learning studies.

To provide a benchmark comparison, the performance of the proposed XGB model was evaluated against Deep Neural Network (DNN) and Natural Gradient Boosting (NGB) models using the same dataset, chronological train-test split, and evaluation metrics. The comparative evaluation results presented in Table 5 indicate that the XGB model achieved the best overall performance among the evaluated models, obtaining the lowest MAE (0.26009 MW) and RMSE (0.47537 MW), as well as the highest R^2 value (0.99499). These results suggest that XGB was

Table 5: Comparative Performance of Prediction Models

Model	**MAE**	**RMSE**	**R^2**
NGB	0.91072	1.38087	0.95788
DNN	0.62750	0.88066	0.98282
XGB	0.26009	0.47537	0.99499

more effective in capturing the nonlinear relationships between geothermal operational parameters and electricity generation output than the alternative models considered in this study. Based on this comparative evaluation, XGB was selected for further SHAP-based explainability analysis. To further assess the stability of the selected XGB model, an additional 5-fold TimeSeriesSplit cross-validation experiment was conducted.

Table 6: TimeSeriesSplit Cross-Validation Results of the XGB Model

Fold	**MAE**	**RMSE**	**R^2**
1	0.49503	0.94870	0.98102
2	0.37473	0.63413	0.99142
3	0.29361	0.46744	0.99551
4	0.28560	0.48776	0.99468
5	0.26312	0.46540	0.99531
Mean ± Std	0.34242 ± 0.09518	0.60068 ± 0.20679	0.99159 ± 0.00613

To further evaluate model stability, a 5-fold TimeSeriesSplit cross-validation experiment was conducted using the optimized XGB model. The results are presented in Table 6. Across the five temporal validation folds, the model achieved an average MAE of 0.34242ś0.09518 MW, an average RMSE of 0.60068 ± 0.20679 MW, and an average R^2 of 0.99159 ± 0.00613. The relatively small standard deviations and consistently high R^2 values indicate that the predictive performance of the XGB model remained stable across different temporal partitions of the dataset. These findings provide additional evidence that the reported performance was not solely dependent on a single train-test split.

3.3. Actual and Predicted Electricity Generation Analysis

To further evaluate the predictive capability of the developed model, comparisons between actual and predicted electricity generation values were conducted using scatter plots and time-series visualizations.

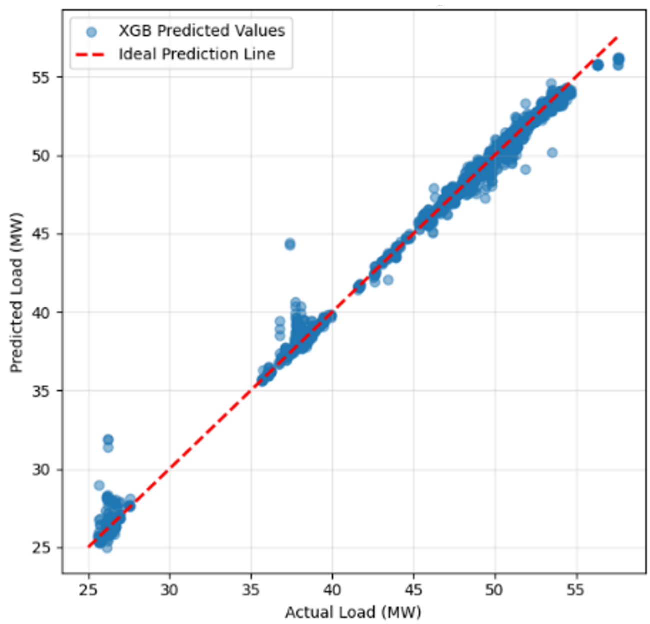

Figure 4. Actual versus Predicted Electricity Generation Using XGB

Figure 4 illustrates the relationship between actual and predicted electricity generation values. Most observations are concentrated near the ideal prediction line, indicating that the predicted values closely match the actual measurements. The limited deviation from the reference line demonstrates the ability of the XGB model to accurately estimate electricity generation under various operating conditions. The strong alignment between actual and predicted values further supports the high R^2 value obtained during model evaluation.

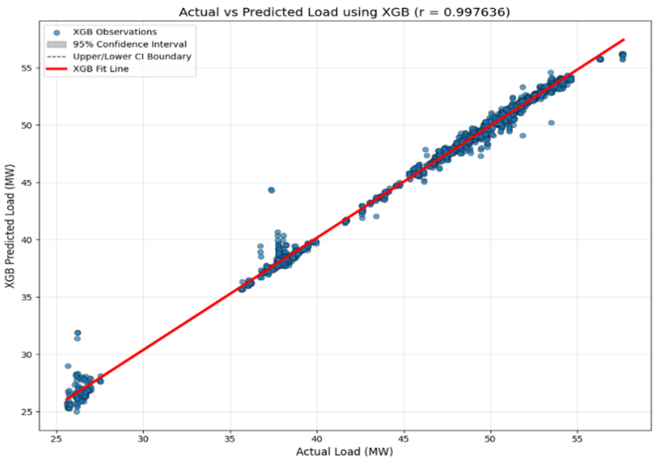

Figure 5. Correlation Between Actual and Predicted Electricity Generation

The correlation analysis between actual and predicted load values was conducted to further evaluate the reliability of the proposed XGB model. As illustrated in Figure 5, the predicted values closely followed the actual observations, indicating strong agreement between the model outputs and measured electricity generation. The Pearson correlation coefficient obtained was 0.997636, demonstrating an extremely strong positive relationship between actual and predicted load values. These results further support the capability of the proposed XGB model to capture the nonlinear relationships between geothermal operational parameters and electricity generation output.

Table 7: Correlation and Determination Metrics

Metric	**Value**
Pearson Correlation (r)	0.9976
Coefficient of Determination (r^2)	0.9953

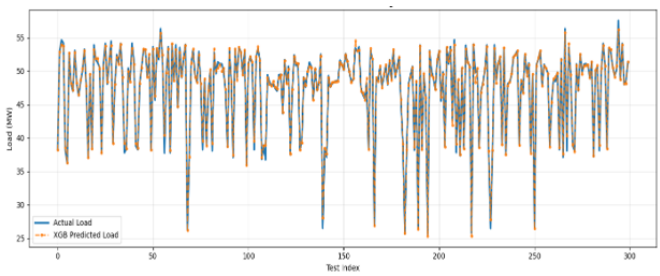

Figure 6. Actual and Predicted Electricity Generation Sequence

Figure 6 presents the comparison between actual and predicted electricity generation values throughout the testing period. The predicted values closely follow the actual generation trend and successfully capture both short-term fluctuations and long-term operational patterns. This result demonstrates the capability of the proposed XGB model to maintain promising predictive performance on the testing dataset while preserving stable prediction behavior across different operating conditions.

3.4. Error Analysis

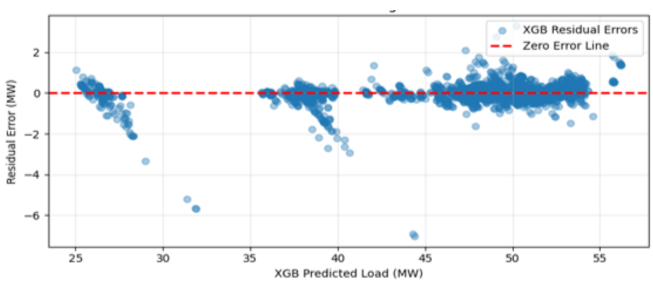

Figure 7. Residual Plot of the XGB Model

Figure 7 shows the residual distribution of the XGB model. The residuals are distributed around the zero-error line without noticeable systematic patterns, indicating that the model predictions are unbiased. Furthermore, the absence of significant clustering or trend structures suggests that the model adequately captured the relationships between the input variables and electricity generation output. The relatively small magnitude of residual errors is consistent with the low MAE and RMSE values reported in Table 5.

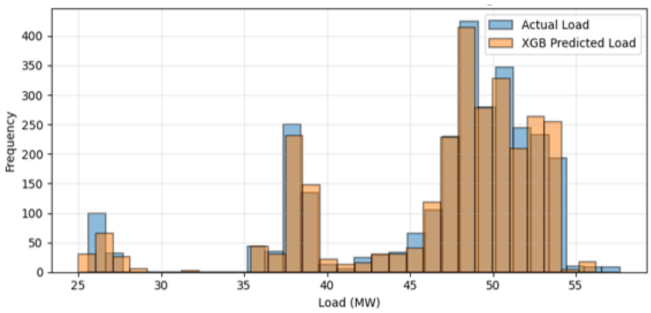

Figure 8. Distribution of Actual and Predicted Electricity Generation

Figure 8 compares the distributions of actual and predicted electricity generation values. The predicted distribution closely follows the actual distribution, indicating that the model preserves the statistical characteristics of the original data. This finding further confirms the reliability of the proposed XGB model in representing the underlying data distribution and producing realistic prediction outputs.

3.5. SHAP-Based Explainability Analysis

In addition to prediction accuracy, model interpretability was analyzed using SHapley Additive exPlanations (SHAP). SHAP provides quantitative information regarding the contribution of each feature to the prediction results and enables both global and local interpretation of the developed machine learning model.

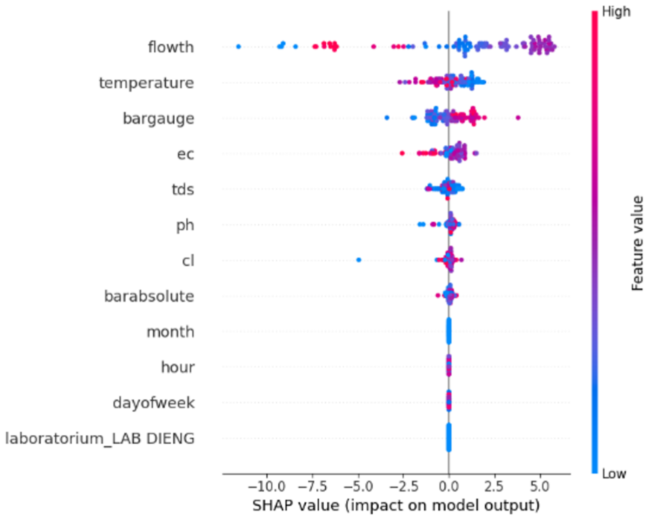

Figure 9. SHAP Summary Plot

3.5.1 Global Featyre Importance Analysis

Figure 9 presents the SHAP summary plot generated from the XGB model. The plot illustrates the influence of each feature on electricity generation prediction across all analyzed samples. Features positioned at the top of the plot have greater influence on the prediction output than those positioned lower in the ranking. The color distribution indicates the magnitude of the feature values, while the horizontal position represents the contribution of each feature to the prediction results. Based on the SHAP summary plot, steam flow rate was identified as the most influential variable affecting electricity generation prediction. This finding is consistent with geothermal power plant operating principles, where steam availability directly affects turbine performance and power generation capacity. Pressure-related variables and temperature also contributed substantially to the prediction results, indicating their importance in describing geothermal operating conditions. Figure 10 shows the global feature importance ranking generated using SHAP values. The ranking confirms that steam flow rate contributed the most to electricity generation prediction, followed by pressure-related variables and temperature. In contrast, chemical parameters such as pH, electrical conductivity, chloride concentration, and total dissolved solids exhibited relatively smaller contributions compared with thermodynamic variables. These results indicate that operational parameters directly associated with steam production and turbine inlet conditions play dominant roles in determining electricity generation output. To complement the global interpretation provided by Figures 9 and 10, a local SHAP explanation was further analyzed for an individual prediction instance.

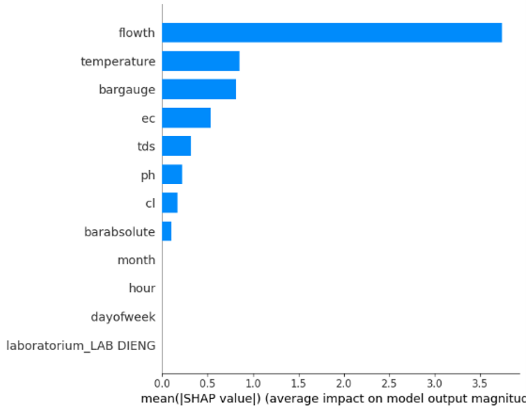

Figure 10. SHAP Feature Importance Ranking

The relatively lower contribution of chemical variables, including pH, electrical conductivity, chloride concentration, and total dissolved solids, may be attributed to their indirect relationship with electricity generation. Unlike steam flow rate, pressure, and temperature, which directly influence turbine inlet conditions and power production, chemical parameters primarily describe fluid characteristics and reservoir geochemistry. Consequently, their influence on short-term electricity generation is less pronounced than that of thermodynamic variables. Similar observations have been reported in previous geothermal machine learning studies, where operational and thermodynamic parameters were found to have stronger predictive relevance than geochemical indicators. It should also be noted that the findings of this study may be influenced by the characteristics of the investigated geothermal field. Since the model was developed using operational data from a single geothermal power plant, the relative importance of the input variables may vary across geothermal reservoirs with different geological conditions, reservoir characteristics, and operational practices. Furthermore, seasonal variations and long-term reservoir changes were not explicitly investigated in the present study. Therefore, the generalizability of the proposed framework to other geothermal fields and operating environments should be interpreted with caution. Compared with previous geothermal forecasting studies that primarily focused on prediction accuracy, the proposed XGB-SHAP framework provides additional explainability by quantifying the contribution of individual operational parameters to electricity generation prediction. This capability may improve model transparency and support operational interpretation, enabling plant operators to better understand the factors that influence generation performance under different operating conditions.

3.6. Local Feature Contribution Analysis

Figure 11 illustrates a local explanation for an individual prediction instance. The SHAP values indicate how each feature contributed positively or negatively to the final prediction. Features with positive SHAP values increased the predicted electricity generation, whereas features with negative SHAP values reduced the predicted output. The local explanation demonstrates the capability of SHAP to provide detailed insight into individual predictions. Such information can assist plant operators in understanding the operational factors that influence electricity generation under specific conditions, thereby supporting more transparent and interpretable decision-making processes.

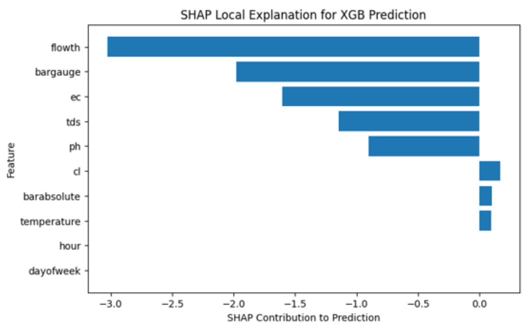

Figure 11. SHAP Local Explanation

4. CONCLUSION

This study proposed an explainable machine learning framework based on Extreme Gradient Boosting (XGB) and SHapley Additive exPlanations (SHAP) for electricity generation prediction in geothermal power plants. The framework utilized operational parameters obtained from the turbine inlet system, including thermodynamic and chemical variables, to model the complex relationships affecting electricity generation output.

The experimental results demonstrated that the proposed XGB model achieved strong predictive performance, obtaining an MAE of 0.26009 MW, RMSE of 0.47537 MW, and R^2 of 0.99499. These results indicate that the model was able to accurately capture the nonlinear interactions among geothermal operational parameters while maintaining promising predictive performance within the evaluated operational environment.

Furthermore, the SHAP-based explainability analysis enhanced model transparency by identifying the relative contribution of each feature to the prediction results. The analysis revealed that steam flow rate and pressure-related variables were the most influential factors affecting electricity generation prediction. Both global and local SHAP explanations provided valuable insights into the model decision-making process, enabling a more comprehensive understanding of how operational conditions influence electricity generation output.

Overall, the proposed XGB-SHAP framework demonstrated high predictive performance and improved model interpretability within the evaluated operational environment. The findings suggest that the framework has potential to support electricity generation analysis and enhance understanding of the operational factors influencing geothermal power generation. However, the present study was conducted using operational data from a single geothermal power plant, which may limit the generalizability of the findings to other geothermal fields and operating conditions. Although benchmark comparisons with DNN and NGB models were included, broader benchmarking with additional machine learning approaches such as Random Forest, LightGBM, CatBoost, Support Vector Regression (SVR), and Long Short-Term Memory (LSTM) networks may provide a more comprehensive assessment of predictive performance across different modeling paradigms. In addition, statistical validation techniques such as multiple-run experiments, confidence interval estimation, and statistical significance testing were not incorporated in the current investigation. Therefore, broader benchmarking and additional statistical validation are required before stronger conclusions regarding model stability and operational applicability can be established. Future research may address these limitations by investigating multiple geothermal fields, alternative machine learning algorithms, and additional operational parameters to further assess the generalizability and reliability of the proposed framework.

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