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Energy loss prediction using least absolute shrinkage and selection operator regression and SHAP explainability

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ABSTRACT

Technical energy loss estimation in power distribution systems is essential for improving operational efficiency and cost-effectiveness. However, distribution-level datasets are often failed to cope with the nonlinear behavior and sparse, low-resolution data typical in modern grid environments. This study proposes an interpretable artificial intelligence (AI) framework based on least absolute shrinkage and selection operator (LASSO) regression integrated with Shapley additive explanations (SHAP) to estimate and explain technical energy losses at the feeder level. An exploratory multicollinearity assessment using correlation analysis and variance inflation factor (VIF) revealed severe redundancy among operational variables, justifying the adoption of L1-regularized regression. Hyperparameter tuning via LassoCV identified an optimal regularization parameter, resulting in strong predictive performance. Comparative evaluation with nonlinear models, including random forest and gradient boosting, demonstrated that LASSO achieves competitive or superior generalization performance while preserving interpretability. Feature importance analysis and SHAP-based explanations confirmed that operational loading variables particularly infeed energy, load factor, and maximum demand are the dominant drivers of technical losses. SHAP dependence and interaction analyses further revealed context-dependent behavior among correlated predictors, enriching interpretability beyond coefficient-based rankings. The results demonstrate that regularized linear modeling, when combined with explainable AI techniques, provides a robust, transparent, and practically deployable solution for technical loss estimation in distribution networks.

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1. INTRODUCTION

Energy losses in power distribution systems represent a significant challenge for utility companies, impacting both operational efficiency and financial performance [1]. These losses, often classified as technical and non-technical, arise from resistive and reactive components within the distribution infrastructure [2]. Accurate estimation of technical losses is essential for identifying inefficiencies and implementing corrective measures such as reduce carbon footprints [3]. Traditional methods such as load flow analysis and statistical models have been widely used for technical losses estimation [4]. However, such approaches often struggle to cope with the increasing complexity of modern electrical networks shaped by distributed energy resources, dynamic loads, and smart grid technologies, especially in the presence of sparse, noisy, and low-resolution real-world data [5].

In addition to limited granularity, distribution-level operational variables often exhibit strong structural interdependence [6]. Parameters such as load factor, loss factor, maximum demand, and energy throughput are physically coupled through fundamental electrical relationships. This induces severe multicollinearity, which can destabilize conventional regression models and obscure reliable feature interpretation [7]. Therefore, robust modeling approaches must not only address sparsity but also manage redundancy within highly correlated predictor sets.

In response to these challenges, artificial intelligence (AI) has emerged as a promising alternative, offering data-driven modeling capabilities suitable for high-dimensional, nonlinear, and sparse datasets [8]. Nevertheless, a major limitation in current AI applications for power systems is the reliance on high-resolution or idealized datasets. Therefore, there is a paucity of studies focusing on its application to technical energy loss estimation in power distribution networks [9]. In countries like Malaysia, power utilities often collect feeder-level data at low sampling rates, typically every 15 or 30 minutes. Such coarse temporal resolution limits the ability to effectively capture technical loss patterns and complicates feature relevance analysis. Furthermore, the presence of missing values, measurement noise, and correlated operational variables reduces the effectiveness of many conventional machine learning (ML) models [10], [11]. Although advanced ML techniques such as random forests, extreme gradient boosting (XGBoost), and neural networks have demonstrated strong predictive capability, they often require large, high-quality datasets and involve high computational complexity, limiting their practicality in constrained utility environments [12]. In addition, these models generally operate as “black box” systems, reducing transparency and limiting stakeholder trust in operational decision-making [13].

Among existing ML models, least absolute shrinkage and selection operator (LASSO) regression stands out due to its dual capability of feature selection and regularization, enabling the construction of regularized models with improved interpretability [14]. LASSO have been employed for their ability to perform both variable selection and regularization, enhancing model interpretability and predictive accuracy. For instance, studies have demonstrated the effectiveness of LASSO in forecasting electricity spot prices by identifying key explanatory variables from large datasets [15]. In power system analysis, LASSO has been applied for various tasks, including fault detection [16] and state estimation [17], [18]. However, the application of LASSO for feeder-level technical energy loss estimation remains limited. Moreover, while LASSO improves global interpretability through coefficient-based analysis, it does not explicitly explain instance-level feature contributions or nonlinear interaction behavior under varying operational conditions.

Furthermore, although nonlinear ensemble methods such as random forest and gradient boosting are frequently employed for energy-related prediction tasks, their performance advantages in low-resolution, highly structured feeder datasets remain uncertain. A systematic comparison is therefore necessary to determine whether additional nonlinear complexity yields meaningful improvements over regularized linear modeling, particularly when interpretability and deployment practicality are key considerations. To address the interpretability limitation of ML-based prediction models, explainable artificial intelligence (XAI) techniques have gained increasing attention. Among these methods, Shapley additive explanations (SHAP) provides a theoretically grounded framework for interpreting model predictions by quantifying the contribution of each feature based on cooperative game theory [19]. SHAP enables both global and local interpretability, allowing detailed analysis of how operational variables influence prediction outcomes. SHAP values [19] provide a way to interpret the contribution of each feature to individual predictions, offering a detailed view of model behavior. Existing studies have primarily applied SHAP in areas such as energy consumption forecasting and anomaly detection in smart buildings [20], [21]. While XAI techniques have been explored in power systems [20], [21], the integration of SHAP with LASSO regression to explain feature selection and model predictions for energy loss estimation is relatively unexplored.

This study addresses that gap by proposing a novel AI-based methodology tailored for the low-resolution data environments. The proposed methodology integrates LASSO regression for feature selection with SHAP to both predict technical energy losses and interpret the influence of operational features using real-world 11 kV feeder data. Although LASSO and SHAP are individually well-established techniques, their combined application for interpretable feeder-level technical energy loss estimation using sparse, low-resolution operational utility data remains relatively underexplored. This combination is particularly well-suited for sparse, real-world datasets due to LASSO’s ability to produce compact models that highlight the most relevant operational features, while SHAP provides transparent and consistent insights into how each feature contributes to the predicted energy losses. These methods offer a balanced trade-off between predictive performance, computational efficiency, and model transparency, making it particularly suitable for low-resolution and operationally constrained utility datasets. Furthermore, the proposed framework is benchmarked against nonlinear ensemble models, namely random forest and gradient boosting, to evaluate predictive capability and interpretability trade-offs. Thus, the primary contributions of this study are as follows:

i) Proposing an interpretable AI framework that integrates LASSO regression with SHAP explainability for feeder-level technical energy loss estimation in power distribution systems.
ii) Demonstrating how L1-regularized regression can effectively mitigate severe multicollinearity and perform embedded feature selection in highly correlated operational feeder datasets.
iii) Providing explainable insight into the influence and interaction of operational and infrastructure variables through SHAP-based global and local interpretability analysis.
iv) Benchmarking the proposed LASSO-SHAP framework against nonlinear ensemble models, namely random forest and gradient boosting, to evaluate predictive performance, generalization capability, and interpretability trade-offs.

2. METHOD

This section outlines the step-by-step process used to develop and train a predictive model for technical energy loss estimation. Specifically, the model utilizes LASSO regression and SHAP analysis, which are tailored to handle low-resolution operational data. The brief workflow of this proposed model is depicted in Figure 1.

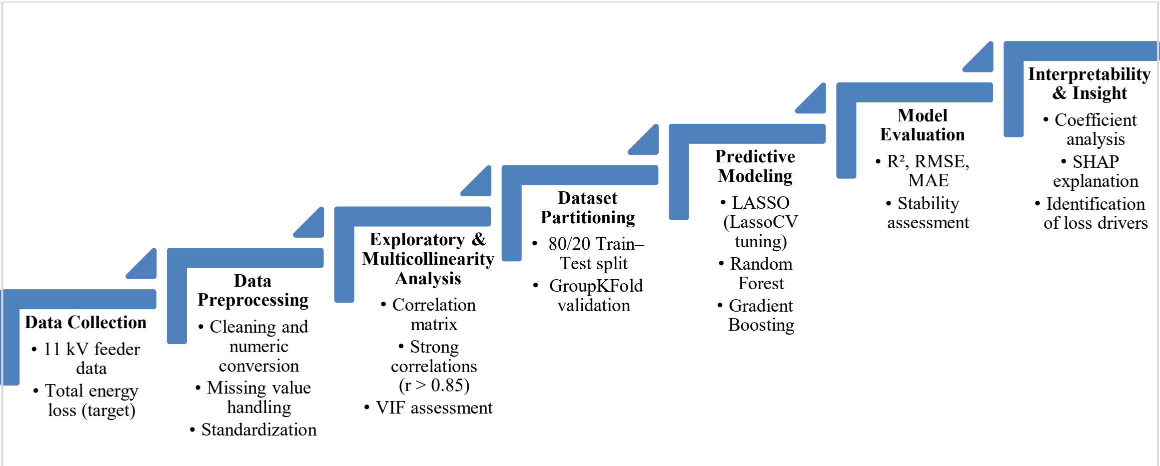


Figure 1. Workflow of proposed model

2.1. Data collection and preprocessing

Data used in this study were obtained from real-world 11 kV medium-voltage feeders operated by a Malaysian utility company. The directly available variables from utility records are: i) monthly infeed energy (MWh), ii) feeder maximum demand (MW), iii) 11 kV feeder number, iv) feeder cable length (km), v) number of distribution transformers, and vi) transformer rated capacity (MVA). These parameters represent the physical and operational characteristics of each feeder and form the basis for technical loss analysis.

2.1.1. Derived feature construction from data collection

In addition to directly measured parameters, several engineering features were derived using established power system formulations to enable technical loss estimation. These derived variables are deterministic transformations of the measured data and are consistent with conventional distribution loss modeling practices. Thus, the feature or parameters crucial for energy loss estimation in distribution systems, includes: i) feeder cable length (km), ii) number of transformers, iii) peak power losses (MW), iv) maximum demand (MW), v) no-load losses (MWh), vi) power (MW), vii) infeed energy (MWh/month), viii) load factor (ratio of average to peak load) and loss factor, ix) full-load losses (MW), x) transformer capacity factor, and xi) estimated total energy losses (MWh) - target variable.

2.1.2. Spatiotemporal dataset structure

The dataset captures a 24-hour operational window, recorded at 15-minute intervals, thereby providing 96 normalized data points per feeder per day. Such temporal granularity aligns with common data recording practices in Malaysian distribution networks, where low-frequency sampling is standard due to infrastructure and cost constraints [22]. In addition, the study network comprises 10 primaries 11 kV underground feeders. Each feeder consists of multiple line sections and load points supplying distribution transformers.

Although the system contains 10 primary feeders, the effective modeling dataset consists of 155 network segments. Each segment represents a physically distinct portion of the distribution network and is treated as an independent observational unit in the loss estimation framework. With 96-time intervals per operational day, the total number of spatiotemporal observations becomes $N = 96 \times 155 = 14{,}880$.

2.1.3. Data preprocessing

To ensure data quality and enhance model robustness, a series of preprocessing steps as shown in Figure 2 were applied to the dataset. First, data cleaning was performed by removing non-numeric entries such as column headers, unit labels, and footnotes. Since LASSO regression is a supervised learning method operating exclusively on numerical inputs, all variables were coerced into numeric format. All fields were then strictly cast to numeric types to prevent silent coercion errors, following best practices outlined [23]. Second, missing data were handled using a hybrid strategy. Time-based interpolation was applied to continuous operational features, while domain-specific logic, such as assigning zero to transformer count when a feeder was offline, was used where applicable. For isolated missing values, median imputation was adopted to reduce the influence of outliers, as recommended [24]. The target variable was defined as: y = total energy losses (MWh), and all remaining columns were treated as predictor variables. Lastly, all numeric features were standardized using z-score normalization through the StandardScaler function. This step was particularly important for LASSO regression, which is sensitive to feature scale due to its penalization mechanism [14]. This preprocessing pipeline was crucial in preparing the dataset for downstream ML tasks. It ensured data consistency, reduced noise, and improved the performance and reliability of the LASSO regression and SHAP explainability models deployed later in the analysis.

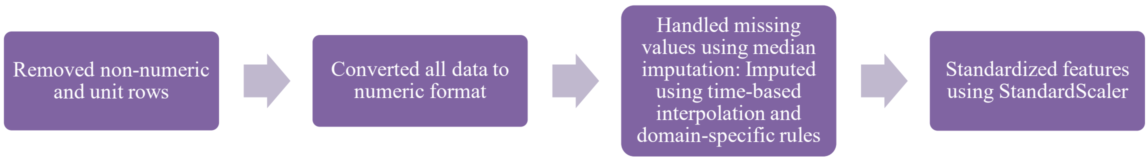


Figure 2. Summary of preprocessing step

2.2. Exploratory analysis and multicollinearity assessment

After data cleaning and preprocessing, a Pearson correlation matrix was computed using all numerical variables. The correlation matrix was visualized via a heatmap to facilitate qualitative assessment of linear relationships among electrical and operational parameters. To quantitatively identify potentially problematic redundancy, absolute pairwise correlation coefficients exceeding a threshold of 0.85 (excluding self-correlations) were extracted and ranked. This threshold was selected to detect strong linear dependencies that may destabilize regression coefficients or inflate variance.

While correlation analysis identifies pairwise linear associations, it does not fully capture multivariate dependency structures. Therefore, variance inflation factor (VIF) analysis was performed to quantify the degree of multicollinearity among predictors. For each explanatory variable, VIF was calculated by regressing that variable against all remaining predictors and computing the inflation factor associated with its coefficient variance.

This exploratory assessment was deliberately conducted before applying LASSO regression. The purpose was threefold: first, to justify the need for regularization-based modeling; second, to demonstrate the presence of feature redundancy and structural interdependence; and third, to ensure statistical rigor in model design. By establishing evidence of multicollinearity, the suitability of LASSO regression with its L1 penalty that promotes sparsity and mitigates collinearity effects is theoretically supported.

2.3. Feature selection and predictive modeling using LASSO regression

The proposed methodology leverages LASSO regression to perform simultaneous feature selection and predictive modeling of total energy loss (MWh). This approach is particularly valuable in power system applications where input variables such as load profiles, transformer ratings, and cable lengths often exhibit multicollinearity [25]. In such environments, conventional ordinary least squares regression can produce unstable coefficient estimates and inflated variance. LASSO addresses this issue by incorporating L1-regularization, which penalizes absolute magnitude of regression coefficients and promotes sparsity [14].

Mathematically, LASSO solves the optimization problem as shown in (1), where y_i is the total energy loss, X_i are the input features, β are the feature weights and λ (or equivalently α) is the regularization strength. The L1 penalty promotes sparsity by shrinking less informative coefficients toward zero and eliminating irrelevant features entirely. This sparsity produces a more regularized model that is easier to interpret and less prone to overfitting, especially when working with complex and high-dimensional datasets [26]. In the context of power distribution systems, such sparsity improves computational efficiency without compromising accuracy, enabling better estimation of TL and more reliable demand prediction [27]. The baseline model provided a reference point to assess the influence of hyperparameter optimization on predictive performance and feature sparsity.

$$\hat{\beta} = \arg min\beta(\frac{1}{2n}\sum_{i=1}^{n}(y_i - X_i\beta)^2 + \lambda\sum_{j=1}^{p}|\beta_j| \quad (1)$$

Compared with ridge regression, which retains all predictors while shrinking coefficient magnitudes, LASSO additionally performs embedded feature selection by driving less informative coefficients toward zero. This property is particularly advantageous for highly correlated feeder-level operational variables where interpretability and variable prioritization are important. Furthermore, unlike principal component analysis (PCA)-based dimensionality reduction, LASSO preserves the original physical meaning of input variables, enabling direct engineering interpretation of feature contributions to technical energy losses.

The dataset was partitioned into training and testing subsets using an 80/20 split. The testing subset was strictly held out during model training and hyperparameter selection to provide an unbiased estimate of generalization performance. To further assess robustness, 5-fold cross-validation was applied to the training set. Cross-validation reduces partition bias and provides a more stable estimate of predictive capability across multiple data splits. Model performance was evaluated using mean squared error (MSE) and the coefficient of determination (R^2), where R^2 measures the proportion of variance in energy losses explained by the model.

A baseline LASSO model was first trained using a fixed regularization parameter (α=0.1). This baseline allowed evaluation of coefficient sparsity and predictive accuracy prior to hyperparameter optimization. Because the choice of α directly controls the bias–variance trade-off, hyperparameter tuning was subsequently performed using LassoCV from the scikit-learn library. A logarithmically spaced alpha grid consisting of 100 candidate values ranging from 10^{-5} to 10^{0} was evaluated using 5-fold cross-validation on the training set. The optimal regularization parameter was selected by minimizing the mean cross-validation MSE. The final selected alpha value was 1×10^{-5}, corresponding to the best trade-off between predictive accuracy and coefficient sparsity. Larger α values may induce underfitting by overshrinking coefficients, whereas overly small α values may reduce sparsity and increase variance. The selected α therefore represents an optimal balance between model complexity and generalization capability.

After identifying the optimal regularization strength, a final LASSO model was retrained on the training data and evaluated on the independent test set. Feature importance was derived directly from the magnitude of the regression coefficients. Because LASSO enforces sparsity, features with zero coefficients were considered non-influential and effectively removed from the model. The absolute value of each non-zero coefficient was used to quantify its relative contribution to energy loss prediction. Positive coefficients imply that increasing the feature increases predicted losses, and negative coefficients indicate an inverse relationship. This direct interpretability aligns well with engineering analysis, enabling physical insight into loss behavior.

2.4. Model interpretability using Shapley additive explanations

To explain the contribution of each feature, SHAP were applied to provide transparent, post-hoc explanations of feature contributions. Specifically, the SHAP explainer was utilized, as it is optimized for linear models such as LASSO and efficiently leverages the model's internal structure to compute additive feature attributions [19]. SHAP summary plots were generated to visualize both the relative ranking of features and the directionality of their impact on predicted energy losses. Bar plots of mean absolute SHAP values were used to rank features according to their average contribution magnitude. A representative subset of training samples was used to compute SHAP values to ensure computational efficiency while preserving interpretive fidelity.

Additionally, SHAP dependence plots were generated for selected key variables to examine marginal effects on predicted energy losses. These plots reveal how feature values influence prediction magnitude and allow identification of potential nonlinear response patterns or threshold behaviors. SHAP interaction values were also computed to estimate pairwise feature interactions, thereby enabling analysis of coupled electrical relationships that may influence technical loss dynamics. By integrating SHAP into the modeling workflow, the approach transforms the LASSO model from a black box into an explainable AI system, thereby supporting more informed decision-making. This aligns with the growing emphasis on trustworthy and interpretable AI in power system applications, especially when dealing with operational and safety-critical infrastructure [28].

All experiments were conducted in Python using scikit-learn for model development and SHAP for explainability analysis. Random seeds were fixed to ensure reproducibility of data partitioning and model training. The integration of group-aware validation, comparative modeling, and explainable AI techniques provides a robust and interpretable approach for technical loss estimation in power distribution systems. This methodology ensures both predictive rigor and engineering interpretability.

2.5. Benchmark comparison with ensemble models

Three regression models were evaluated: LASSO regression, random forest regression, and gradient boosting regression. For LASSO, a pipeline was constructed integrating median imputation, feature standardization, and L1-regularized linear regression using LassoCV for automatic hyperparameter selection. Standardization was applied because L1-regularization is scale-sensitive, ensuring equitable penalization across features. The regularization parameter α was selected via internal 5-fold cross-validation over a logarithmically spaced grid, balancing sparsity and predictive accuracy. LASSO solves penalized least-squares optimization problem in which an L1 penalty term promotes coefficient shrinkage and embedded feature selection.

Random forest was implemented with median imputation and 300 decision trees without depth constraints, enabling flexible nonlinear modeling through bagged ensemble aggregation. Gradient boosting was configured with 200 estimators, a learning rate of 0.05, and a maximum tree depth of 3, sequentially minimizing residual errors to improve bias–variance trade-offs. Model performance was evaluated using MSE, mean absolute error (MAE), and the R^2. Both hold-out test performance and mean GroupKFold cross-validation R^2 were reported. Grouped validation is essential in feeder-based studies, as it evaluates generalization to unseen feeders. Differences between single-split and grouped R^2 were interpreted as indicators of model stability.

Feature importance was derived according to model structure. For LASSO, importance was based on absolute coefficient magnitude, with sign indicating directionality. For rando forest and gradient boosting, impurity-based importance scores were used to quantify each feature's contribution to prediction error reduction.

3. RESULTS AND DISCUSSION

This section presents the experimental results of the proposed technical loss estimation framework. Feature correlations and multicollinearity are first analyzed to justify the use of regularized regression. The predictive performance of the LASSO model is then evaluated, followed by SHAP-based interpretability analysis. Finally, a comparative assessment with nonlinear models is conducted to examine performance and explainability trade-offs.

3.1. Correlation and multicollinearity analysis

The correlation matrix in Figure 3 and Table 1 reveals a highly structured and strongly interdependent feature space. Several near-perfect correlations were identified, indicating severe redundancy among key operational variables. Table 1 highlights severe redundancy among loading-related variables, particularly between load factor and loss factor (r =0.9989), indicating strong structural dependency within the feeder operational dataset. This is physically plausible, as loss factor is closely related to load factor through demand–loss relationships. Including both in a conventional regression model would therefore produce unstable coefficient estimates due to redundancy.

Similarly, infeed energy (MWh/month) and number of transformers show an extremely strong correlation (r =0.9942). This indicates that feeders supplying larger monthly energy volumes tend to require more transformer installations, reflecting infrastructure scaling with demand. Such a relationship is consistent with distribution planning principles, where transformer deployment increases proportionally with load aggregation. However, statistically, this near-perfect correlation introduces severe redundancy.

Strong correlations were also observed between load factor and number of transformer (r =0.8726), as well as between loss factor and number of transformer (r =0.8647). These relationships indicate that operational loading characteristics are structurally linked to network size and transformer configuration. Collectively, the correlation matrix reveals that load intensity, infrastructure scale, and energy throughput are tightly coupled variables rather than independent predictors.

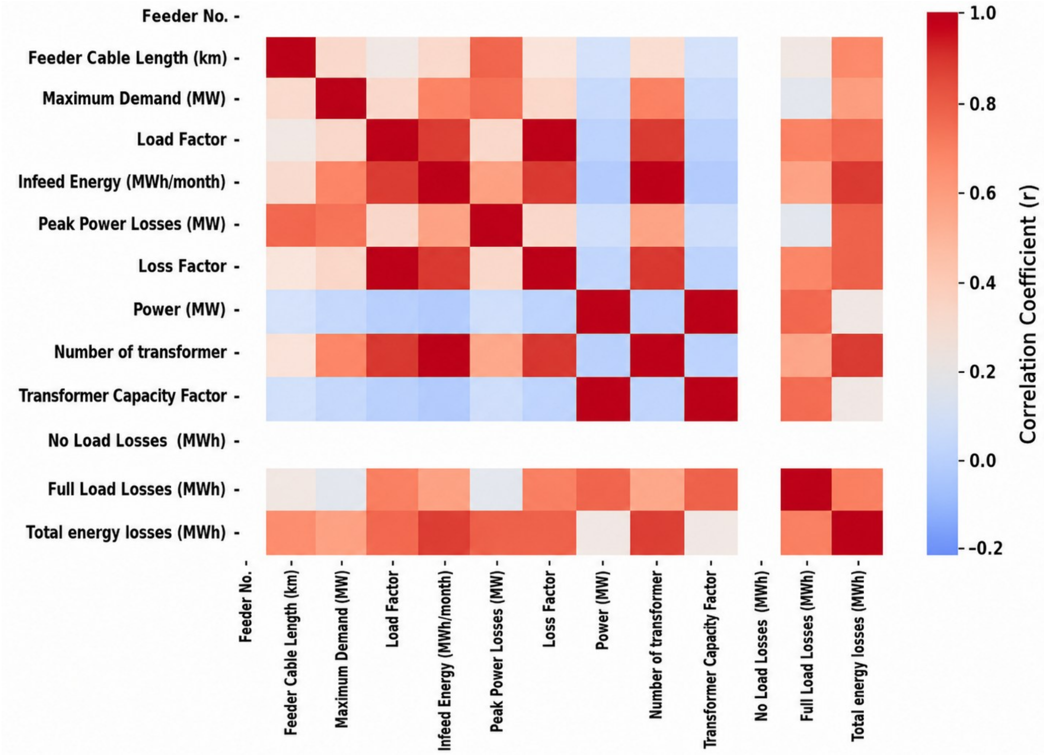


Figure 3. Feature correlation matrix

Table 1. Strong pairwise correlations among operational variables (r >0.85)

Feature 1	Feature 2	r
Load factor	loss factor	0.9989
Infeed energy (MWh/month)	number of transformers	0.9942
Load factor	number of transformers	0.8726
Loss factor	number of transformers	0.8647

The severity of multicollinearity is further confirmed by the VIF results depicted in Table 2. VIF values exceeding 10 indicate severe multicollinearity. Most operational variables greatly exceeded this threshold, justifying the use of regularized regression techniques.

Table 2. Variance inflation factor result

Feature	VIF
Power (MW)	1.25×10^{2}
Transformer capacity factor	9.79×10^{1}
Load factor	1205.144244
Loss factor	821.923614
Number of transformers	310.422958
Infeed energy (MWh/month)	199.667306
Maximum demand (MW)	55.125709
Peak power losses (MW)	36.746916
Feeder cable length (km)	18.848296
Full load losses (MWh)	17.793737

Power and transformer capacity factor exhibit infinite VIF values, indicating perfect linear dependence. Such conditions make ordinary least squares regression mathematically unstable due to singular matrix inversion. Load factor and loss factor display extremely high VIF values (1205.14 and 821.92), far exceeding conventional multicollinearity thresholds (VIF >10). Number of transformer and infeed energy also show very large VIF values (310.42 and 199.67), while maximum demand, peak power losses, and feeder cable length remain elevated. These results indicate systemic multicollinearity across the feature space rather than isolated redundancy.

Such interdependence is expected in power distribution systems, where variables related to loading, demand, and losses are physically coupled through I-squared-R (I^2R) behavior. Load factor, maximum demand, peak losses, and energy throughput represent interconnected manifestations of underlying electrical dynamics. Therefore, the observed multicollinearity reflects intrinsic system behavior rather than data quality issues.

In conventional linear regression, this level of multicollinearity would yield unstable and inflated coefficients. This justifies the use of LASSO regression, which applies L1-regularization to shrink redundant coefficients and select representative predictors among highly correlated groups. Consequently, LASSO stabilizes estimation while preserving interpretability. Overall, the correlation and VIF analyses confirm severe structural redundancy, providing strong justification for adopting regularized regression to ensure robust and interpretable technical loss estimation.

3.2. Feature selection using least absolute shrinkage and selection operator regression

Figure 4 presents the actual vs. predicted values plot for the LASSO regression model, comparing true technical energy loss values with model predictions before and after hyperparameter tuning. The black dashed line represents the ideal case where predictions exactly match actual values. The baseline model (α=0.1) exhibits noticeable dispersion around the diagonal line, indicating moderate predictive performance and slight underfitting.

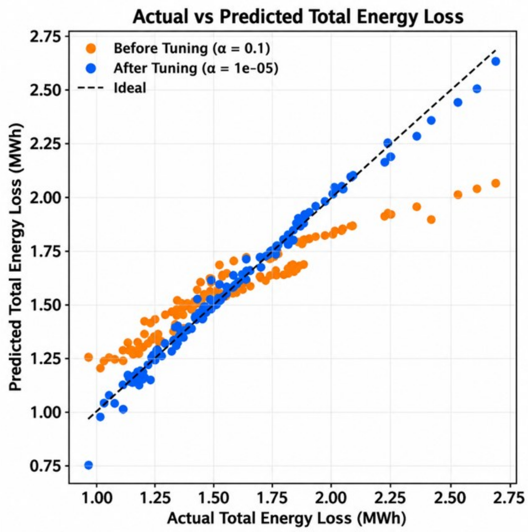


Figure 4. Actual vs. predicted values for LASSO regression (before vs. after tuning)

As summarized in Table 3, the baseline configuration selected only four features and achieved R^2 values of 0.7725 (test) and 0.7730 (5-fold cross-validation), with an MSE of 0.0258. The relatively large regularization parameter imposed stronger coefficient shrinkage, reducing variance but limiting the model's ability to capture the full linear structure in the data. Hyperparameter tuning was subsequently performed using LassoCV over a logarithmically spaced grid of alpha values ranging from $1e^{-5}$ to 1 with 5-fold cross-validation. The optimal alpha was identified as $1e^{-5}$, corresponding to minimal regularization. This result suggests that the dataset contains a strong linear signal and sufficient sample size (14,880 observations), allowing the model to retain most informative predictors without excessive shrinkage.

Following tuning, the LASSO model achieved substantial performance improvement, with test R^2 =0.9889, cross-validated R^2 =0.9881, and MSE =0.0013. The tuned model retained nearly all relevant features, indicating that many predictors contribute meaningfully to total energy loss estimation under low regularization. The tight clustering of points around the diagonal in Figure 5 confirms strong agreement between predicted and actual values.

Table 3. Comparison of before tuning and after tuning using LASSO regression

Parameter	Before tuning	After tuning
Alpha value	0.1	$1e^{-5}$
Selected features	4	Many (almost all)
MSE	0.0258	0.0013
R^2 (test)	0.7725	0.9889
R^2 (5-fold cross-validation mean)	0.7730	0.9881

The small optimal alpha value does not indicate overfitting; rather, it reflects the presence of strong linear relationships within well-preprocessed data. The consistency between test and cross-validated R^2 further demonstrates model stability across different data partitions. The use of 5-fold cross-validation mitigates partition bias and confirms that performance is not dependent on a single train–test split.

Figure 5 presents the LASSO coefficient magnitudes after tuning (α=1e^{-5}). Infeed energy exhibits the largest coefficient magnitude, followed by load factor and maximum demand. This confirms that cumulative energy throughput and operational loading intensity are the dominant drivers of technical energy losses. From a physical standpoint, this is consistent with power system theory, where total energy losses are fundamentally governed by current magnitude and duration. Higher infeed energy reflects sustained current flow, while load factor and maximum demand capture utilization consistency and peak loading stress, respectively. These variables collectively represent the operational regime of the feeder and therefore naturally dominate loss behavior.

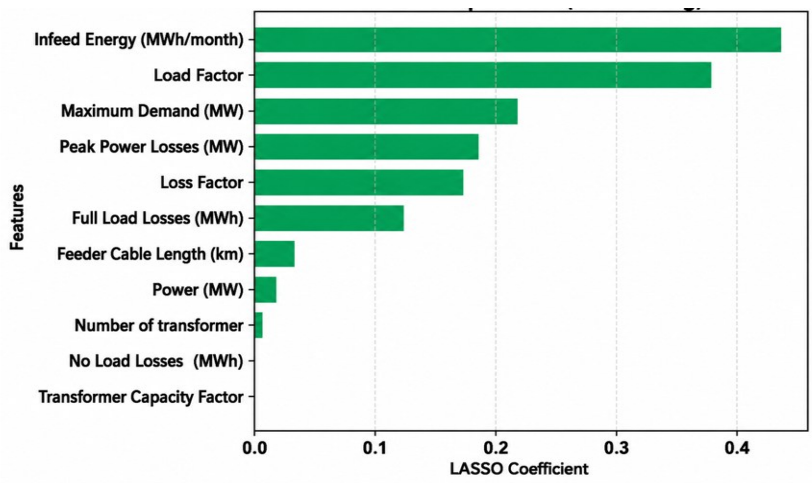


Figure 5. Feature importance for LASSO regression after tuning

Peak power losses and loss factor also demonstrate substantial contributions, further reinforcing the strong influence of loading characteristics on loss estimation. Peak losses reflect instantaneous thermal stress, whereas loss factor scales peak demand effects over time. Their non-zero coefficients suggest that temporal loading distribution contributes meaningfully to total energy dissipation.

In contrast, infrastructure-related variables such as feeder cable length and number of transformer exhibit comparatively smaller but still positive coefficients. This indicates that while structural design parameters influence losses through resistance and transformer core losses, their effect is secondary once operational loading variables are accounted for. This hierarchy aligns with engineering intuition: infrastructure establishes the loss baseline, but loading behavior amplifies it.

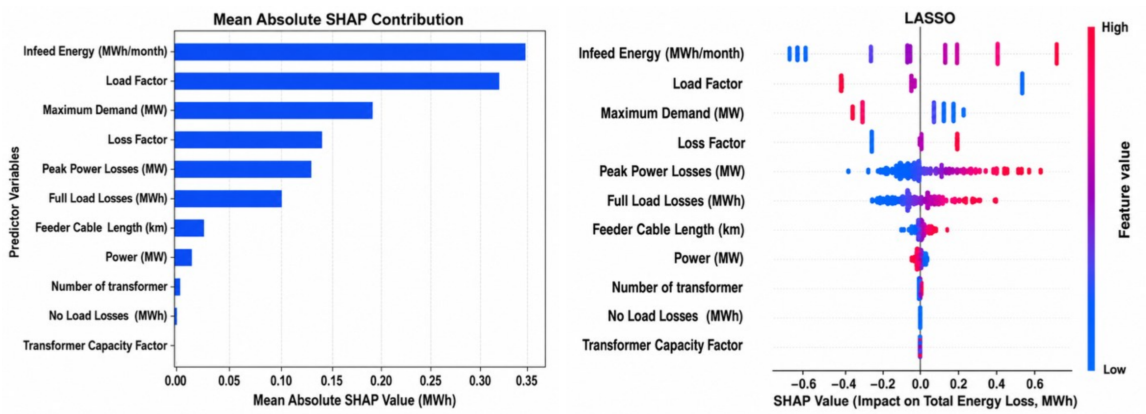
Notably, power, no load losses, and transformer capacity factor show negligible or near-zero coefficients. This suggests that their explanatory power is either redundant with stronger predictors or statistically absorbed through correlated variables such as infeed energy and maximum demand. Given the earlier multicollinearity findings (extreme VIF values), this shrinkage behavior is expected. LASSO selectively retains the most informative representative within highly correlated feature groups while suppressing redundant predictors, thereby stabilizing coefficient estimates. The overall coefficient distribution confirms that the dataset is predominantly governed by linear operational dynamics rather than complex nonlinear interactions. The relatively small optimal regularization parameter (α=1e^{-5}) indicates that most features contain meaningful signal, yet the model still performs implicit redundancy control by moderating less influential predictors.

Importantly, because coefficient sign represents directionality, all retained features exhibit positive associations with total energy losses. This monotonic relationship is physically consistent: increases in loading, demand, infrastructure scale, or energy throughput should logically increase resistive and conversion losses. The absence of strong negative coefficients further supports the physical coherence of the model.

Overall, the LASSO results demonstrate that the dataset is predominantly governed by linear loading dynamics. The model achieves high predictive accuracy while maintaining direct interpretability through coefficient-based feature importance. The embedded sparsity mechanism confirms that LASSO functions not only as a predictive tool but also as a structured diagnostic framework for identifying operationally significant drivers of technical losses [14].

3.3. Explainable artificial intelligence insights using Shapley additive explanations

To enhance interpretability of the LASSO regression model beyond global coefficient magnitudes, SHAP was applied to evaluate the contribution of each input feature toward the prediction of total energy loss. The SHAP summary plot ranks features based on their average impact across all predictions, as depicted in Figure 6. Figure 6(a) presents the feature contribution ranking based on mean absolute SHAP values, while Figure 6(b) illustrates the distribution of SHAP values across different feature magnitudes. Features appearing higher in the SHAP ranking contribute more strongly to model predictions. Positive SHAP values indicate increased predicted energy losses, whereas negative SHAP values indicate reduced contribution to the predicted losses. In the summary plot, red-colored points represent higher feature values and blue-colored points represent lower feature values. Features with SHAP values farther from zero exert stronger influence on the predicted technical energy losses, whereas values closer to zero indicate weaker contribution.



(a) (b)

Figure 6. Global SHAP analysis of the LASSO regression model for (a) feature contribution ranking based on mean absolute SHAP values and (b) SHAP summary plot showing the influence of feature values on predicted energy losses

The analysis indicates that infeed energy is the most influential predictor of total energy losses. This is physically consistent with power system theory, as cumulative energy throughput directly reflects the magnitude and duration of current flow, which governs resistive losses via the I^2R mechanism. Features capturing sustained loading behavior, such as load factor and maximum demand also exhibit substantial SHAP contributions, confirming that operational intensity exerts stronger predictive influence than purely structural parameters.

Infrastructure-related variables, including feeder cable length and number of transformers, show moderate but consistent positive SHAP contributions. The monotonic behavior observed for cable length aligns with resistive loss principles: longer conductors introduce higher impedance, increasing cumulative losses [29]. Transformer count similarly contributes positively, reflecting the aggregation of no-load and conversion losses across multiple units [30]. Each transformer introduces core (no-load) losses and copper (load) losses, which can accumulate as more units are introduced [31]. However, once demand-driven effects are accounted for, their incremental contribution appears secondary compared to loading variables.

While the summary plot provides global importance ranking, several features particularly load factor and loss factor exhibit mixed SHAP contributions (both positive and negative values). This pattern suggests context-dependent influence rather than purely additive behavior. A wider spread of SHAP values indicates that the feature influence varies across different operating conditions, suggesting context-dependent behavior within the feeder network.

Unlike the SHAP summary plot, dependence plots in Figure 7 illustrate how the prediction changes as a single feature increase or decrease, while also revealing interaction effects with related variables. To investigate this further, SHAP dependence plots of load factor and loss factor were generated to analyze conditional feature effects as shown in Figure 7(a). The dependence analysis reveals that the impact of loss factor intensifies under high maximum demand conditions. When peak demand is elevated, increases in loss factor correspond to amplified SHAP values, indicating stronger contribution to predicted energy losses. This interaction is physically interpretable, as energy loss is approximately proportional to the squared peak demand scaled by a temporal loss factor. This is expected, as during peak demand, higher currents flow through the network, amplifying resistive losses [32]. These findings reinforce that peak demand management is crucial in reducing losses and optimizing energy efficiency in distribution systems [33]. Thus, loss factor does not act independently but modulates the effect of peak loading.

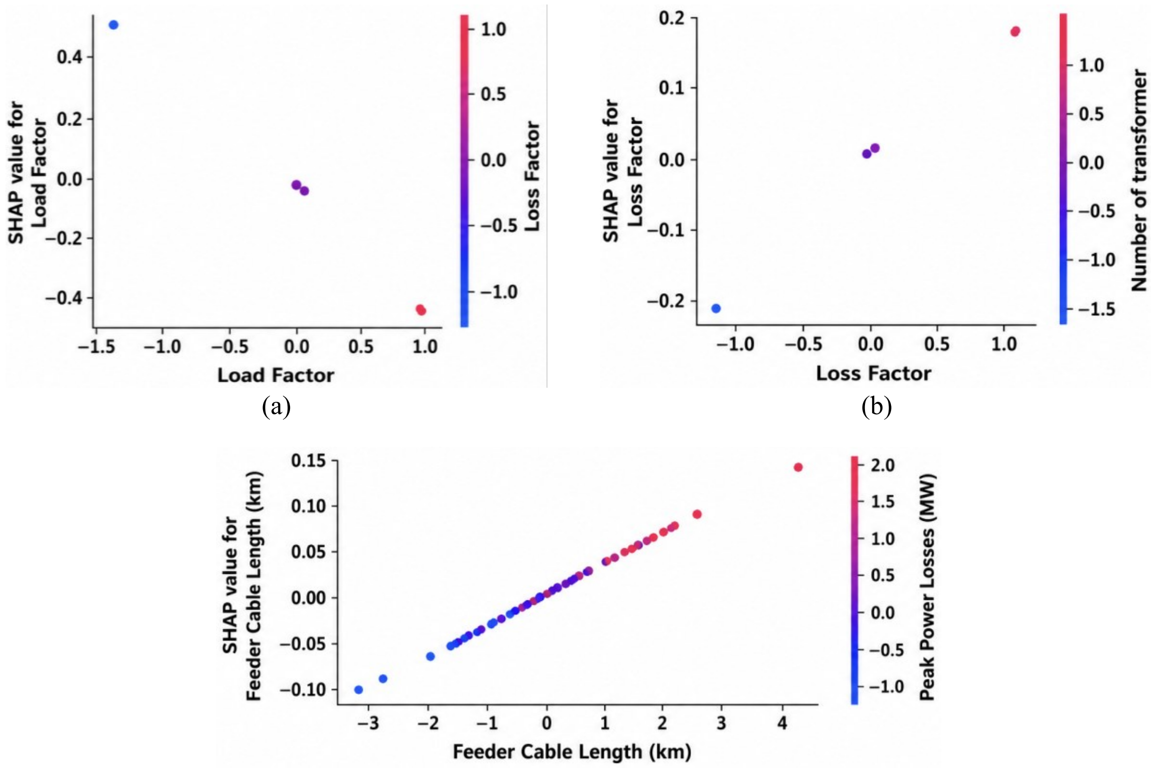
Similarly, load factor demonstrates nonlinear conditional behavior. Under moderate demand conditions, its SHAP values are relatively compressed; however, at higher loading regimes, its contribution becomes more pronounced. This suggests that sustained utilization amplifies cumulative losses only when the system operates near higher demand thresholds. Therefore, load factor functions as an operational amplifier rather than a dominant standalone driver. An additional interaction pattern of dependence plot observed in Figure 7(b) indicate that the marginal contribution of transformer counts increases when loss factor is higher, confirmed by [34], implying that infrastructure expansion disproportionately elevates baseline losses under high magnetizing loss conditions. This highlights a structural-operational coupling effect that would not be visible through coefficient magnitude alone.

In contrast, feeder cable length in Figure 7(c) exhibits largely monotonic SHAP behavior, with limited interaction sensitivity. This confirms its predominantly linear physical relationship with losses through network resistance [35]. However, the magnitude of its contribution increases under elevated power levels, reinforcing the combined influence of conductor length and current magnitude.

The color gradient represents the interacting feature value, enabling visualization of coupled operational effects. The observed SHAP behavior is better explained by the nature of the LASSO algorithm and its interaction with the data. LASSO applies L1-regularization, which encourages sparsity by shrinking many regression coefficients toward zero [14]. Since SHAP values in linear models are directly derived from model coefficients, this shrinkage results in relatively small and tightly packed SHAP outputs [36]. Furthermore, LASSO, being a linear model, lacks the ability to capture nonlinear relationships and feature interactions, which further limits the variability and expressiveness of SHAP explanations. Nevertheless, this limitation is well-compensated by SHAP's ability to uncover complex dependencies and contextual behavior, offering a more complete picture of the model's behavior across different operating conditions.

For instance, features like loss factor, infeed energy, and load factor exhibited both positive and negative SHAP values, depending on their value ranges and interactions with other features. This suggests that while they may have low average importance in LASSO, they possess context-dependent significance, potentially influenced by seasonal load patterns or network topology. Such results highlight the added value of SHAP in capturing feature dynamics that are not immediately obvious through traditional regression-based analysis. This highlights the utility of SHAP in uncovering nuanced behaviors and providing deeper insight into feature dynamics [19]. Moreover, the low alpha value used in LASSO ($1e^{-5}$) aligns with the SHAP analysis, indicating that most features have at least some degrees of relevance and should be considered in interpretative frameworks. While LASSO effectively performs global feature selection, SHAP enhances explainability by decomposing the model's prediction at a granular level, making it particularly suitable for operational decision-making in power systems. This dual-perspective approach ensures that both strategic (global) and tactical (local) insights can be extracted to support evidence-based interventions in grid management.

Additionally, the preprocessing step of standardizing all features using StandardScaler contributes to the apparent flattening of SHAP values. While standardization ensures that all predictors are on the same scale, it also compresses the dynamic range of SHAP values in visual outputs [37]. Another plausible explanation is featuring multicollinearity. When predictor variables are highly correlated (e.g., estimated maximum demand and average power loss), SHAP tends to distribute importance among them rather than attributing dominance to one feature, leading to a diluted individual contribution [38]. This effect, however, reflects the real-world operational complexity of power systems, where multiple factors often act in concert. The findings emphasize that operational loading characteristics particularly cumulative energy throughput and sustained demand are the primary determinants of total energy losses. These suggest that loss mitigation strategies should prioritize: i) demand-side management and peak load reduction to control cumulative I^2R losses, ii) optimization of feeder utilization to improve load factor efficiency, and iii) strategic infrastructure planning, including transformer deployment and feeder length optimization, to minimize baseline resistive losses. By leveraging explainable AI methods, this study provides a data-driven framework that not only improves prediction accuracy but also enhances trust and transparency in model decisions, a crucial factor for adoption in the power utility sector [28]. In doing so, it bridges the gap between AI-driven analytics and practical engineering application, offering scalable insights that align with real-world decision-making processes.



(a) (b)

(c)

Figure 7. SHAP dependance plots for the LASSO regression model for (a) interaction between load factor and loss factor, (b) interaction between loss factor and number of transformers, and (c) interaction between feeder cable length and peak power losses

3.4. Comparison of LASSO regression with gradient boosting and random forest

To address the concern that LASSO is inherently linear and may not capture nonlinear relationships in complex grid environments, a comparative analysis was conducted using nonlinear ML models, namely random forest and gradient boosting. All models were evaluated under a group-aware validation framework using feeder-level splits to prevent data leakage and ensure robust generalization assessment. Performance was measured using test R^2, root mean square error (RMSE), MAE, and group k-fold cross-validation R^2 to reflect predictive accuracy and stability across different feeders. These results are recorded in Table 4.

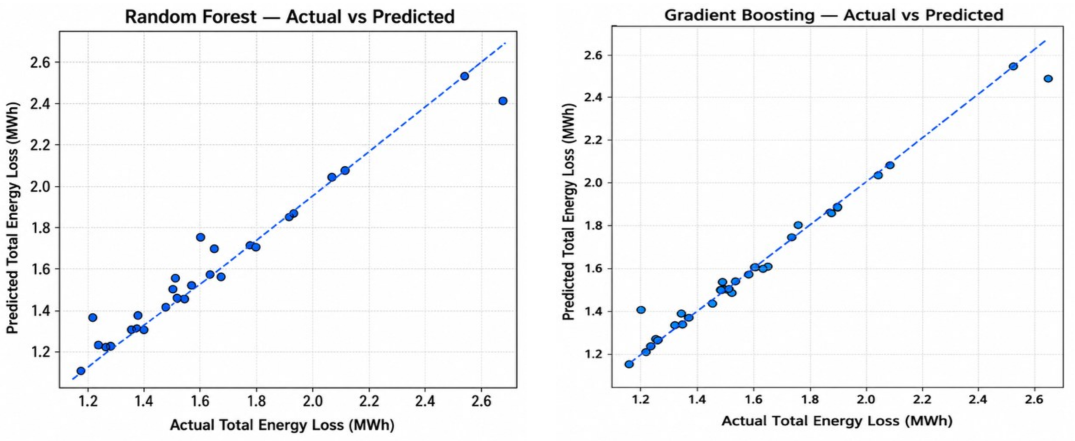
Table 4. Performance comparison between LASSO, random forest, and gradient boosting

Model	R^2	RMSE	MAE	Group CV R^2 (mean)
LASSO	0.9827	0.0473	0.0316	0.9773
Random forest	0.9581	0.0737	0.0412	0.9019
Gradient boosting	0.9770	0.0545	0.0284	0.9674

The results indicate that LASSO achieved the highest predictive performance, with a test R^2 of 0.9827 and a Group CV R^2 of 0.9773. Gradient boosting demonstrated competitive performance (test R^2 =0.9770; Group CV R^2 =0.9674), whereas random forest showed comparatively lower generalization capability (Test R^2 =0.9581; Group CV R^2 =0.9019). The stronger generalization performance of LASSO under group-aware validation suggests that the dominant relationships governing total energy losses in the dataset are largely linear or near-linear in nature. This finding is physically consistent with distribution system theory, where technical losses scale predictably with current magnitude and loading intensity according to I^2R principles.

Although nonlinear ensemble methods are capable of modeling complex interactions and higher-order effects, the empirical comparison demonstrates that their additional flexibility does not yield substantial performance improvements. In fact, LASSO demonstrated comparatively stronger generalization performance than gradient boosting in both test and grouped cross-validation metrics. This indicates that increased model complexity does not translate into meaningful predictive gains for the studied loss patterns. Although comparative performance metrics indicate that LASSO achieved the strongest observed generalization performance, formal statistical significance testing and confidence interval estimation were not conducted in this study and may be considered in future investigations to further validate inter-model differences.

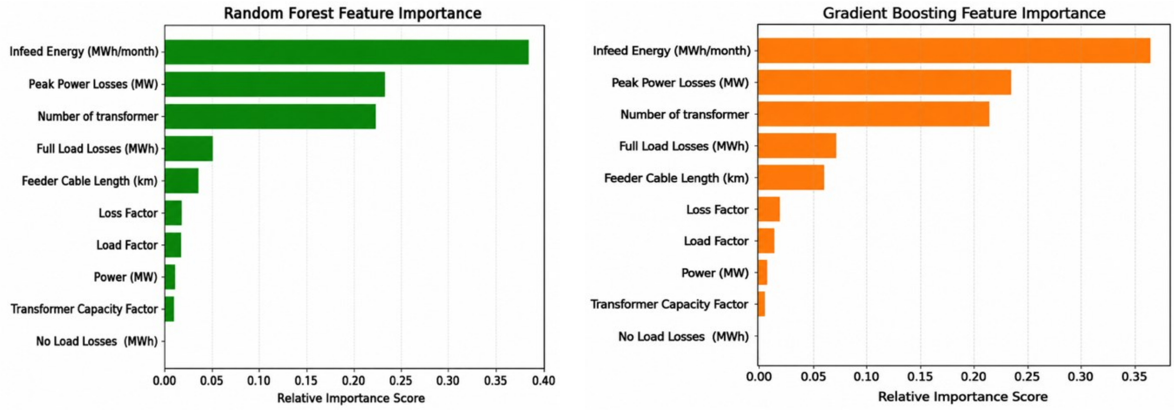
To further examine interpretability trade-offs, SHAP analysis was applied across models. Comparative performance and explainability analysis of random forest and gradient boosting models, as shown in Figures 8 to 10. The actual vs. predicted value using random forest is displayed in Figure 8(a) and gradient boosting is displayed in Figure 8(b). The SHAP summary plots for random forest depicted in Figure 9(a) and gradient boosting depicted in Figure 9(b) revealed similar dominant predictors, primarily infeed energy, load factor, and maximum demand. However, nonlinear models exhibited more dispersed SHAP distributions shown in Figures 10(a) and 10(b), reflecting interaction-driven attribution across correlated variables. In contrast, LASSO produced more structured and stable SHAP contributions, directly aligned with coefficient magnitudes. The interpretability advantage of LASSO is therefore substantial: its linear formulation allows direct physical interpretation of coefficients, while SHAP explanations remain consistent and transparent.



(a) (b)

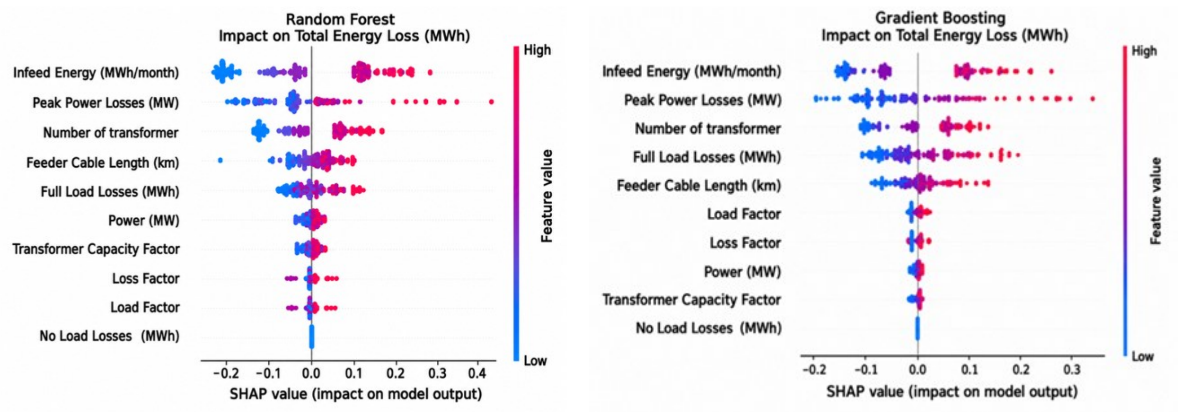
Figure 8. Comparative performance and explainability analysis actual versus predicted values of (a) random forest and (b) gradient boosting models

Although LASSO achieved the strongest observed grouped generalization performance in this study, nonlinear ensemble methods such as gradient boosting may still provide advantages in scenarios involving stronger nonlinear dynamics, heterogeneous feeder behavior, or higher-resolution operational data. This is proven by lower MAE for gradient boosting, suggesting that nonlinear interactions may contribute marginal improvements in localized conditions. These models are capable of capturing localized feature interactions and complex nonlinear dependencies that linear models may not fully represent. However, such flexibility is typically accompanied by increased computational complexity and reduced interpretability. This highlights a trade-off between interpretability and predictive flexibility. In contrast, LASSO provides direct coefficient-based interpretation, embedded feature selection, and greater transparency for engineering analysis. Therefore, the choice between linear regularized models and nonlinear ensemble approaches should consider not only predictive accuracy but also explainability, deployment practicality, and operational trust requirements in utility environments. Importantly, the comparative SHAP analysis did not uncover fundamentally new governing dynamics in the nonlinear models beyond those already identified by LASSO. The primary drivers of total energy losses remained operational loading characteristics rather than complex nonlinear interactions. This suggests that while nonlinear behavior may exist at localized levels, the dominant predictive structure in the dataset is sufficiently captured by a regularized linear model.



(a) (b)

Figure 9. Comparative performance and explainability feature importance of (a) random forest and (b) gradient boosting models



(a) (b)

Figure 10. Comparative performance and explainability impact on total energy loss of (a) random forest and (b) gradient boosting models

Considering both predictive performance and interpretability, LASSO provides an optimal balance for technical loss estimation in distribution networks. It achieves superior generalization performance, effectively handles severe multicollinearity through L1 regularization, and offers transparent feature attribution suitable for engineering decision-making. While nonlinear ensemble models provide modeling flexibility, their marginal performance gains do not justify increased complexity in this application. Therefore, the results support the selection of LASSO as the most appropriate modeling framework for this study.

4. CONCLUSION

This study proposed an interpretable framework for technical energy loss estimation in power distribution systems by integrating LASSO regression with SHAP-based explainability. Correlation and

VIF analyses confirmed severe multicollinearity among operational variables, justifying the use of L1-regularized regression. The proposed model achieved strong predictive performance (test R^2 =0.9827; Group CV R^2 =0.9773) while outperforming random forest and gradient boosting in grouped generalization. SHAP analysis further showed that infeed energy, load factor, and maximum demand are the dominant factors influencing technical energy losses, providing physically meaningful explanations consistent with power system principles. Overall, the proposed framework offers an accurate, stable, and interpretable approach for technical loss estimation using real-world distribution network data. Although the findings are based on a specific utility dataset, the framework provides a practical foundation for explainable AI applications in power distribution systems. Future work will evaluate the proposed approach using larger and more diverse datasets and investigate hybrid physics-informed ML models to further improve prediction accuracy and generalizability.

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AUTHOR CONTRIBUTIONS STATEMENT

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Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
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Siti Azirah Asmai	✓	✓			✓			✓		✓	✓	✓	✓	✓
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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

The authors state no conflict of interest.

DATA AVAILABILITY

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

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