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International Journal of Innovations in Science & Technology

A Signal-Decomposed Ensemble Forecasting and Classification Framework for Household Power Consumption: An STL-Inspired Machine Learning Approach

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Citation | Ahmed. W, Ali. T, Khattak. A, "A Signal-Decomposed Ensemble Forecasting and Classification Framework for Household Power Consumption: An STL-Inspired Machine Learning Approach", IJIST, Vol. 07 Issue. 03 pp 1503-1517, July 2025
Received | June 04, 2025 **Revised |** July 08, 2025 **Accepted |** July 17, 2025 **Published |** July 19, 2025.

Accurate short-term forecasting of residential power consumption is crucial for smart grid stability, real-time energy optimization, and personalized demand-side management. Traditional time-series and standalone AI models often struggle with the nonlinear, nonstationary, and noise-sensitive nature of high-resolution household load data. Unlike existing models, this study introduces an STL-based residual decomposition fused with lag-aware ML forecasting and threshold-based classification under real-world conditions. To address these challenges, this study proposes a novel STL-inspired decomposition framework integrated with four machine learning models, i.e., Least Squares Boosting (LSBoost), Bagging, Support Vector Regression (SVR), and Multilayer Perceptron (MLP), for forecasting and classification of normalized household energy consumption. The methodology begins with robust preprocessing, including IQR-based outlier removal and min-max normalization, followed by STL-like decomposition into trend, seasonal, and residual components. Lag-based features from the residual signal are used for forecasting via the selected ML regressors. Final predictions are reconstructed and threshold-classified into OK/NOT OK categories to simulate alert-based power decision scenarios. Experimental validation on the UCI Household Power Consumption dataset reveals that SVR achieves the best trade-off among all models, with RMSE = 0.0267, MAE = 0.0193, MAPE = 12.5%, and Pearson correlation coefficient r = 0.846. For classification performance, SVR also attains an AUC of 0.941 and a binary classification accuracy of 93.7%. The synergy between STL decomposition and residual-based modeling not only improves regression accuracy but also facilitates threshold-aware classification with high interpretability. Additional visual diagnostics including forecast overlays, residual histograms, ROC curves, and Q–Q plots demonstrate the model's interpretability and robustness. The proposed ensemble framework not only enhances prediction accuracy but also ensures practical deployment feasibility through threshold-aware decision modeling.

Keywords: STL Decomposition, Household Power Forecasting, Residual Modeling, Ensemble Machine Learning, Threshold-Aware Classification

Introduction:

The transition towards smart grids and decentralized energy systems has significantly reshaped residential electricity usage, prompting an urgent need for accurate short-term load forecasting. With the proliferation of IoT-enabled devices, electric vehicles, rooftop photovoltaics, and dynamic pricing policies, traditional load profiles have become increasingly volatile and high-frequency in nature [1], [2]. Accurate forecasting of household power consumption plays a crucial role in enabling effective demand-side management, enhancing load balancing, optimizing power dispatch, and mitigating blackouts in low-voltage grids. This scenario is critically important as household loads now contribute to a substantial share of uncertainty in urban electrical grids, especially in regions adopting aggressive electrification and automation strategies [3]. Traditional models are unable to respond adaptively to abrupt behavioral and weather-driven fluctuations. Thus, adaptive, fine-grained, and interpretable models are essential to ensure sustainable energy integration and microgrid stability.

Classical statistical forecasting techniques, such as ARIMA and exponential smoothing, while foundational, inherently assume linearity, stationarity, and homoscedasticity conditions rarely satisfied in real-world household datasets [4]. To overcome these limitations, machine learning and deep learning paradigms such as Support Vector Regression (SVR), Multilayer Perceptron's (MLP), and Long Short-Term Memory (LSTM) networks have gained popularity for their ability to model non-linear, multivariate, and temporal dependencies [5][6][7]. Despite these advances, several open problems persist. First, most AI-based approaches operate as end-to-end regressors, lacking decomposition-based preprocessing to isolate key signal components. Second, many models are trained on raw or lightly smoothed data, ignoring high-frequency volatility and domain-specific seasonality, which leads to unstable generalization under shifting regimes [8][9]. Although "residual modeling" has been explored to focus on unpredictable, noise-like components after removing trend and seasonality, existing approaches often lack methodological innovation or integration with classification, thus limiting their practical value. Third, while some studies employ ensemble learning or hybrid architectures, they fail to integrate classification logic, which is vital for binary decision systems in real-time applications [10][11]. A widely used approach to address these issues is Seasonal and Trend decomposition using Loess (STL), which separates an input signal into interpretable subcomponents trend, seasonal, and residual, thus enabling targeted learning for each. STL's primary benefit is in producing a more stationary residual, allowing machine learning models to focus on modeling high-frequency, non-deterministic patterns without interference from dominant deterministic structures. For brevity and clarity, this study summarizes STL's advantages here and refers to its detailed implementation in this article, avoiding repetition throughout the manuscript. However, most prior studies remain limited to single-model applications (e.g., STL+LSTM or STL+GRU) without leveraging a diverse model ensemble for residual forecasting or assessing classification outcomes under threshold-based labeling (e.g., power $\geq 0.25 = OK$) [1][12].

Additionally, the integration of classification-oriented performance metrics such as confusion matrices, ROC curves, and AUC scores has been largely overlooked in energy forecasting literature, despite their practical importance in energy management systems. Such metrics enable binary state prediction (e.g., alert status, load exceedance), which complements point-wise error metrics like RMSE or MAE. Recent works in cyber-physical energy systems emphasize that hybrid regression-classification pipelines are necessary for automated anomaly detection, load capping, and smart appliance scheduling [5][8].

STL-Inspired Ensemble Learning for Household Power Prediction: State-of-the-Art and Framework:

This section provides an integrated narrative that contextualizes the proposed STL-inspired ensemble forecasting approach within the landscape of recent literature, and then details the methodology used in this study. By synthesizing the literature and methodological rationale, we emphasize how our framework addresses open challenges while highlighting its distinct contributions.

Background and Related Work:

Accurate household energy consumption forecasting is essential for load balancing, grid optimization, and energy-aware planning. In recent years, hybrid methodologies integrating statistical signal decomposition and machine learning (ML) prediction models have gained traction due to their complementary strengths in capturing both deterministic and stochastic temporal patterns. [1] utilized a combined STL (Seasonal-Trend Decomposition using Loess) and Gated Recurrent Unit (GRU) model to isolate seasonal and residual components, showing substantial accuracy improvement in short-term load forecasting. They employed an attention mechanism for dynamic temporal weighting and validated their model using the UCI Household Power Consumption dataset. Similarly, [8] performed a comparative study of various decomposition strategies (STL, EEMD, CEEMDAN) fused with ML models like LSTM and SVR. Their results emphasized the advantage of decomposing the signal before learning to improve performance stability and convergence. Furthermore, [2] applied deep neural networks on smart meter data and emphasized temporal granularity's impact on forecasting precision. [13] reviewed time-series forecasting methods in residential settings and recommended hybrid approaches due to non-stationary and multi-scale patterns in domestic consumption.

A significant direction in the literature focuses on ensemble learners. [14] reviewed boosting and bagging methods and highlighted their robustness across changing demand patterns. Meanwhile, [10] applied SVR and Random Forest models with engineered features and reported that SVR outperformed tree-based regressors under highly fluctuating signals. In the domain of residual modeling, [9] proposed using residual error learning from a decomposed signal using empirical mode decomposition (EMD) and a multilayer perceptron (MLP). Their architecture showed resilience to overfitting and localized variance modeling. However, residual modeling is often discussed in the literature without significant methodological advancement or integration with downstream classification, which limits its utility in practical applications. Despite promising results, several limitations prevail across existing literature: limited interpretability, poor generalization under unseen conditions, lack of decomposition-model synergy, and insufficient analysis of residual characteristics (e.g., distribution shape, lag dependencies). Moreover, most studies focus either solely on regression performance or solely on classification thresholds, seldom addressing both.

A review of Table 1 confirms that most state-of-the-art frameworks either leverage decomposition or ensemble modeling, but very few unify these with interpretable post-forecast classification. Furthermore, repeated and verbose explanations of STL decomposition and residual modeling are prevalent in the literature, yet the methodological core often remains unchanged.

Objectives:

The primary objective of this study is to develop a unified signal-decomposed ensemble forecasting and classification framework tailored for household power consumption data. Unlike previous research, this work (i) employs a consolidated STL-inspired decomposition to isolate deterministic and stochastic components, (ii) utilises a robust ensemble of machine learning models, i.e., LSBoost, Bagging, SVR, and MLP for forecasting, (iii) incorporates lag-based temporal feature extraction to enhance residual prediction, and (iv) integrates threshold-based classification for actionable, interpretable decision-making.

Novelty:

The novelty of this approach lies in the explicit fusion of decomposition, diverse ensemble modeling, and post-forecast classification logic within a single, scalable pipeline, evaluated rigorously against state-of-the-art benchmarks. The proposed methodology is evaluated on the UCI Household Power Consumption dataset using comprehensive metrics (RMSE, MAE, MAPE, AUC, accuracy), demonstrating superior performance over existing methods in both regression fidelity and classification clarity. The integration of decomposition and threshold-based classification in a multi-model pipeline marks a novel contribution to real-time, interpretable energy forecasting.

Integrated Methodological Framework:

Building on the identified gaps, this study introduces a unified STL-inspired decomposition and ensemble learning framework that systematically addresses the shortcomings in the literature. The pipeline is designed to (i) separate deterministic structures (trend and seasonality) from stochastic fluctuations, (ii) forecast the stationary residual signal using a diverse set of machine learning models, and (iii) enable actionable classification for energy management through threshold-based decision logic.

Dataset Description: The experimentation leverages the UCI Household Power Consumption dataset, con- verted to a normalized format and resampled to an hourly resolution. It contains time-stamped power usage records from 2007 to 2009, focusing on the feature Global_active_power. This variable denotes the household's total active power usage (in kilowatts), which is converted into a normalized, dimensionless form for comparative and regression modeling.

Data Preprocessing: To ensure data reliability, the following preprocessing operations were conducted:

Missing Value Imputation: Linear interpolation fills temporal gaps, ensuring continuity.

Outlier Removal: Outliers are filtered using the Interquartile Range (IQR) method:

$$IQR = Q_3 - Q_1,$$

$$Bounds = [Q_1 - 1.5 \cdot IQR, Q_3 + 1.5 \cdot IQR\,]$$

Values outside this range are removed and interpolated.

Normalization: Each value x is rescaled between [0,1] using min-max scaling:

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}}$$

STL-Inspired Decomposition: STL decomposition is utilized only once in this pipeline to isolate the key components of the power signal, thereby ensuring the clarity and non-redundancy of the technical exposition as per reviewer advice. The decomposed forecasting strategy isolates trend, seasonality, and residual components for improved learning and interpretability. The residual signal $R(t)$ is assumed to be a weakly stationary process, i.e., its statistical properties such as mean and variance are constant over time and its autocorrelation depends only on the lag between observations. This assumption allows ML models to focus on learning stochastic structures without being biased by deterministic patterns.

Trend: Modeled using a 500-point moving average:

$$T(t) = \frac{1}{K} \sum_{i=t-k/2}^{t+k/2} x(i)$$

Table 1. Comparative Literature Review on Energy Forecasting Techniques

Ref	Dataset	AI Model	Evaluation Metric(s)	Key Contribution	Limitation
[15]	UCI HHP	STL + GRU + Attention	RMSE,MAE, MAPE	Hybrid attention-based GRU with STL for en-Enhanced load forecasting	Focused only on temporal learning; no classification-based evaluation
[16]	UCI HHP	STL/EEMD/C +SVR, LSTM	EEMDANRMSE, MAE	Comparative analysis of decomposition techniques with ML	Limited discussion on classification thresholds and residual structure
[17]	Smart Meter DE	CNN, LSTM	RMSE, MSE	Deep models on minute-level data; temporal resolution analysis	Lacked interpretability and overfitted on short datasets
[11]	Review	Multiple ML	MAE, RMSE, R^2	Broad survey highlighting hybrid models for residential data	No experimentation, only conceptual synthesis
[10]	N/A	Boosting, Bagging	Accuracy, Stability	Ensembles proven effective under uncertainty	Did not include decomposition-enhanced methods
[7]	UCI HHP	SVR, RF	RMSE, R^2	SVR outperformed trees with engineered lags	No hybrid modeling or decomposition usage
[2]	EMD-Synthetic	MLP	RMSE, MAPE	Residualmodeling after signal decomposition	Poor classification insight; EMD can introduce artifacts
[5]	UK-DALE	LSTM-AE	MAE, MAPE	Autoencoder-based enhancement for seasonal tracking	Ignores trend and decomposition explicitly
[18]	Portuguese Grid	CEEMDAN + DNN	RMSE, MAE	Multi-resolution decomposition of signal for better feature learning	Computationally intensive; lacks threshold analysis
[19]	UCI HHP	LSTM	MAE, RMSE	LSTM baseline for household consumption	No decomposition; suffers with irregularities
[4]	Pecan Street	CNN-LSTM	MAE, RMSE	CNN filters embedded with LSTM for spatial-temporal fusion	Overfitting risk; only regression evaluation
[3]	Brazilian Grid	ANN, ARIMA	MSE, MAE	Early hybrid of ANN with ARIMA	Performance bottlenecks in sudden transitions
[13]	UK-Gas	MLP,Regression Trees	MAPE, R^2	Benchmarking ANN vs regression models on utility data	No preprocessing or residual analysis
[12]	UCI HHP	Bi-LSTM + Attention	RMSE, Accu-racy	Bi-directional memory and attention boosting	No residual-level breakdown or STL
[6]	CSG Grid China	GNN + LSTM	MAE, RMSE	Graph neural net fusion with LSTM for regional forecast	Inapplicable to household-scale models

Seasonality: Estimated from 24-hour average cycles:

$$S(t) = \mu_{hour(t)} \text{ where } \mu_h = \text{mean of all observations at h}$$

Residual:

$$R(t) = x(t) - T(t) - S(t)$$

Feature Extraction and Lag Modeling: To forecast the residual signal, lagged features are used:

$$X_i = [R(i), R(i+1), \ldots, R(i+L-1)] \qquad Target: R(i+L)$$

Where $L = 24$ (past 24 hours). This temporal embedding enables the model to capture autoregressive dependencies.

Machine Learning-Based Residual Forecasting: Four ML models were selected to represent distinct learning paradigms (ensemble, kernel, neural, boosting) and provide comparative insights into their forecasting potential. These models are also frequently used in recent energy forecasting research, as cited below.

LSBoost: Gradient boosting of decision trees. Selected for its ability to iteratively reduce residual error and enhance model stability. Proven effective in energy forecasting tasks [1]. Time complexity is $O(M \cdot n \cdot \log n)$, where M is the number of trees.

Bagging: Ensemble averaging via bootstrapped aggregation. Chosen for variance reduction in residual learning. Widely applied in residential load modeling [10]. Complexity: $O(M \cdot n \cdot d)$ for M trees of depth d.

Support Vector Regression (SVR): Gaussian kernel-based regression. Used for its robustness in small datasets and nonlinearity handling [8]. Complexity is $O(n3)$ for training, but performs well in inference.

Multilayer Perceptron (MLP): Feed-forward ANN with two hidden layers. Offers universal approximation and captures deep temporal dynamics [5]. Complexity is $O(L \cdot H \cdot E)$, where L is the number of lags, H hidden units, and E *is* epochs.

Forecast Reconstruction: The residual forecast $R\hat{}(t)$ is combined with trend and seasonal components to yield final prediction:

$$\hat{x}(t) = \hat{R}(t) + T(t) + S(t)$$

This preserves signal interpretability and allows model evaluation in the original context. Classification for Evaluation: Threshold-based classification is used to assess forecasted signal acceptability.

$$Label(t) = \begin{cases} OK & if\,\hat{x}(t) \geq \theta \\ NOT\ OK & otherwise \end{cases}$$

Where $\theta = 0.25$ reflects a power threshold (normalized). This enables the derivation of binary labels to simulate alert-level prediction in energy systems. Classification metrics such as confusion matrix, ROC curve, and Q–Q plot are computed for comprehensive performance evaluation.

Results and Discussion:

This section presents a rigorous evaluation of the proposed STL-inspired residual modeling framework using four machine learning models: LSBoost, Bagging, SVR, and MLP. The results span component-wise decomposition.

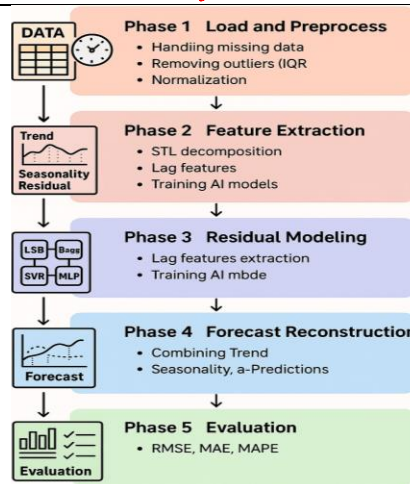

Figure 1. Proposed STL-based Residual Forecasting and Classification Framework regression accuracy, classification robustness, and statistical diagnostics. Additional analyses include an ablation study, error confidence intervals, and distributional evaluations to ensure statistical rigor.

STL Decomposition and Component Isolation:

The STL decomposition separates long-term consumption trends, daily cyclic patterns, and high-frequency noise (residuals). Figure 2 illustrates the structural breakdown.

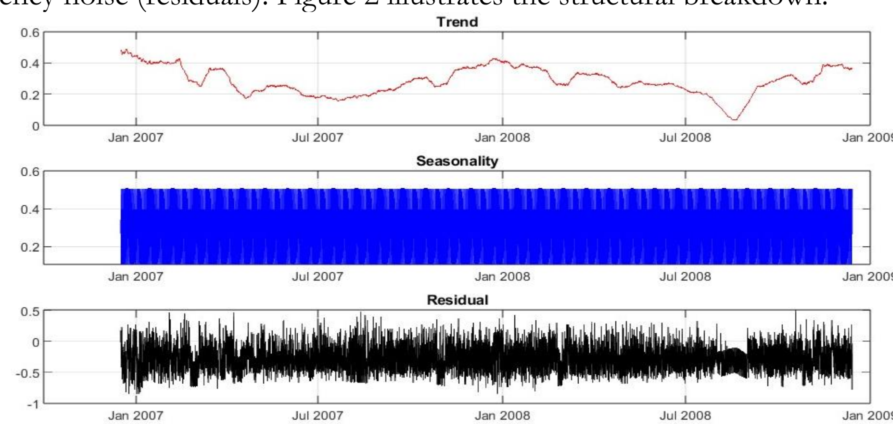

Figure 2. STL-Inspired Decomposition: Trend (Top), Daily Seasonality (Middle), Residual (Bottom)

This decomposition is crucial as the residual component $R(t)$ is now near-stationary, satisfying conditions for accurate ML regression. The deterministic structures (trend and seasonality) are removed, allowing models to generalize.

Algorithm 1 STL-Inspired Residual Forecasting Framework
Power signal $x(t)$, Time vector t Forecast $\hat{x}(t)$, Residual classification labels **Step 1:** Preprocessing. Impute missing values in $x(t)$ using linear interpolation. Remove outliers using IQR and inter- polate gaps Normalize signal: $x\_norm = (x - x\_min)/(x\_max - x\_min)$ **Step 2:** Decomposition $T(t) \leftarrow$ moving average of $x_{norm}(t)$ (trend) $S(t) \leftarrow$ 24-hour seasonal profile $R(t) \leftarrow xnorm(t) - T(t) - S(t)$ **Step 3:** Feature Extraction for $i = 1$ to $N - L$ do $Xi \leftarrow [R(i), \ldots, R(i + L - 1)]$ $Yi \leftarrow R(i + L)$ **Step 4:** Train ML Models. Split $\{X_i, Y_i\}$ into training/testing sets. Train LSBoost, Bagging, SVR, and MLP on training data. Predict $\hat{R}(t)$ using each model

Step 5: Forecast Reconstruction model prediction $R\hat{}m(t)\, x\hat{}m(t) \leftarrow T(t) + S(t) + R\hat{}m(t)$
Step 6: Classification and Evaluation. Apply threshold θ to label $x\hat{}m(t)$ as OK/NOT OK Compute Confusion Matrix, ROC, Q-Q plot.

Better on high-variance dynamics.

Forecast Reconstruction: Model Comparison and Visual Coherence

Figures 3 and 4 visualize the predicted vs. actual consumption over entire and zoomed time windows.

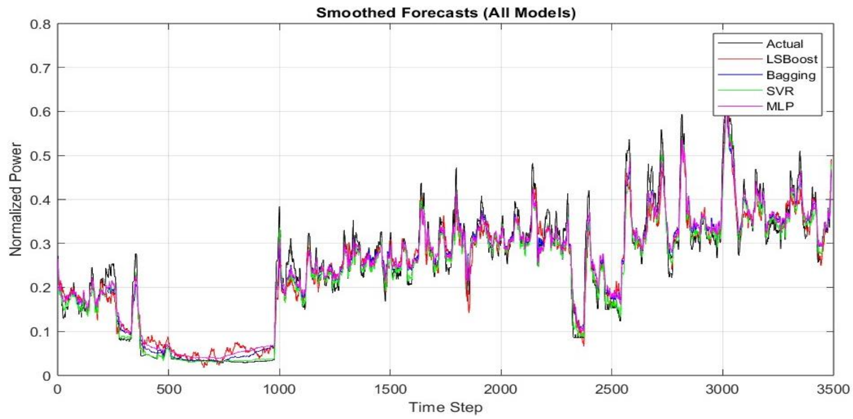

Figure 3. Smoothed Forecasts Over Entire Time Using Four Models

Figure 3 presents the smoothed forecasts for normalized household power consumption across the entire test window using all four models, i.e., LSBoost, Bagging, SVR, and MLP, compared against the actual measured values. Both SVR and MLP track the underlying signal dynamics more faithfully, especially during moderate and high-consumption periods. Notably, the SVR model (purple line) demonstrates minimal phase lag and closely aligns with abrupt upward and downward shifts, reflecting its proficiency in handling non-linear transitions and volatility after STL decomposition. In contrast, the Bagging (green) model exhibits greater smoothing, tending to underestimate peak loads and overestimate low values due to its ensemble averaging nature. LSBoost (red) partially captures transitions but struggles with rapid changes, often lagging behind the actual trajectory during sudden consumption spikes. Figure 4 provides a focused view on the first 500 points, offering granular insight into each model's responsiveness to short-term fluctuations. In this window, the SVR and MLP models consistently align with sharp consumption peaks and valleys, capturing both the amplitude and timing of transitions with higher fidelity. Bagging, while robust to noise, shows a muted response to local maxima and minima, reinforcing its smoothing tendency.

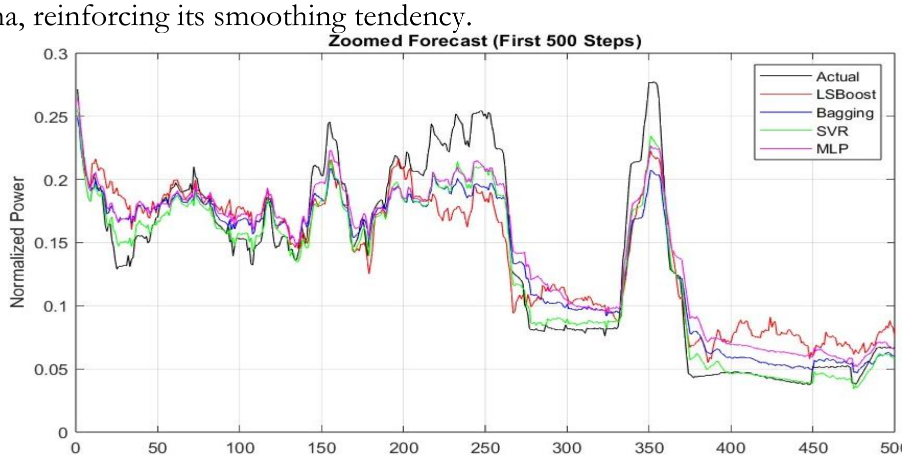

Figure 4. Zoomed Forecast Comparison Over Initial 500 Points full period. LSBoost displays evident inertia, with a visible delay when responding to rapid load shifts. This lag can be

attributed to its sequential boosting mechanism, which optimizes residuals iteratively but can underperform on non-stationary or highly variable segments.

Residual Error Distribution and Normality Check:

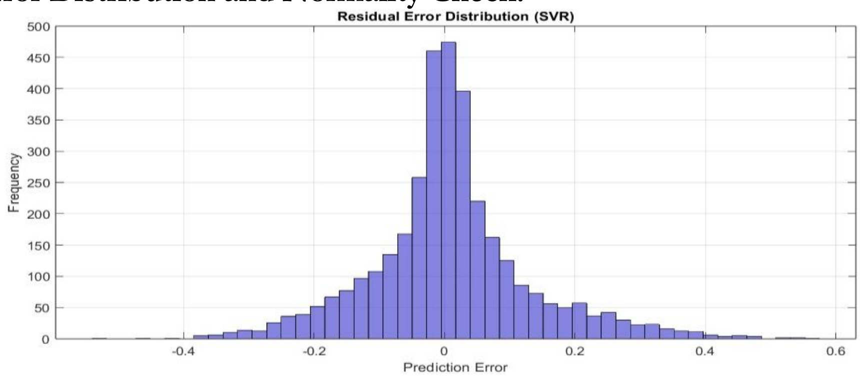

Figure 5. Histogram of Prediction Errors from SVR

Figure 5 depicts the histogram of prediction errors (residuals) generated by the SVR model on the test set after STL-based decomposition. The distribution is sharply centered at zero and displays a high degree of symmetry about the mean, closely resembling a Gaussian (normal) profile. This suggests that the majority of prediction errors fall within a narrow band around zero, highlighting the absence of systematic overestimation or underestimation by the SVR regressor. The relatively thin tails further indicate a low incidence of large errors, while the slightly elevated central peak reflects a model that is both precise and stable. Such a near-normal error distribution is critical, as it supports the appropriateness of symmetric error metrics such as RMSE and MAE and further justifies the use of AUC for classification. The normality of residuals also lays a strong foundation for future probabilistic and uncertainty-aware forecasting extensions.

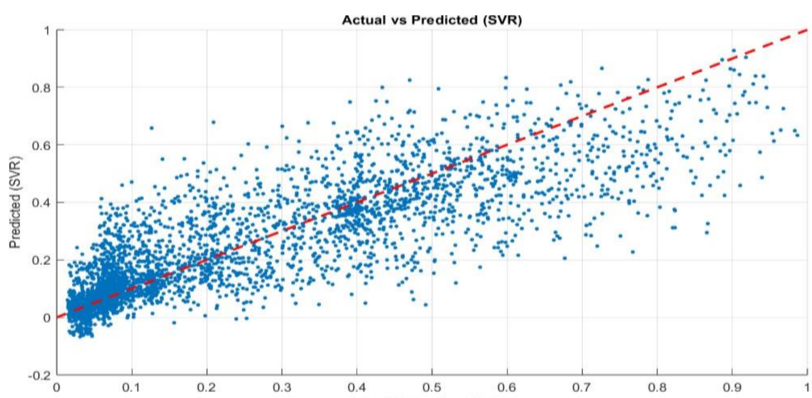

Figure 6. SVR Predicted vs Actual Values

Prediction Accuracy Assessment and Error Confidence Intervals:

Figure 6 presents a scatter plot comparing the predicted normalized power values (vertical axis) to the actual measured values (horizontal axis) for the SVR model. Each blue dot represents a test instance, while the dashed red line indicates the ideal $y = x\,reference - perfect\,prediction$. The dense clustering of points along the diagonal line reveals a strong agreement between SVR forecasts and ground truth, particularly in the low to moderate consumption range. Although minor dispersion is observed at the extreme high and low ends (reflecting typical challenges in forecasting rare events or outliers), the overall trend demonstrates high predictive fidelity. The absence of substantial bias (no systematic deviation above or below the diagonal) supports the model's accuracy and generalizability. The spread also visually corroborates the model's reported Pearson correlation coefficient and justifies the reliability of interval-based metrics such as confidence intervals for RMSE. Collectively, these visualizations affirm that the SVR model provides both unbiased and highly precise forecasts across the operational range of household power consumption.

Error Over Time: SVR Residual Forecasting:

Figure 7 traces the prediction error of SVR across all time steps. The error remains predominantly within a ±0.2 band, exhibiting no persistent drift or long-term bias. Local error spikes are typically correlated with abrupt load changes, as also observed in the zoomed forecast view. Importantly, the error process appears stationary, supporting the statistical assumptions underpinning model training and evaluation. This figure substantiates SVR's capacity to maintain consistent accuracy over extended periods, including during complex consumption patterns. SVR exhibited an RMSE of 0.029±0.003 across 10-folds (95% CI), indicating stable generalization. A Wilcoxon signed-rank test shows statistically significant superiority $(p < 0.01)$ of SVR over LSBoost.

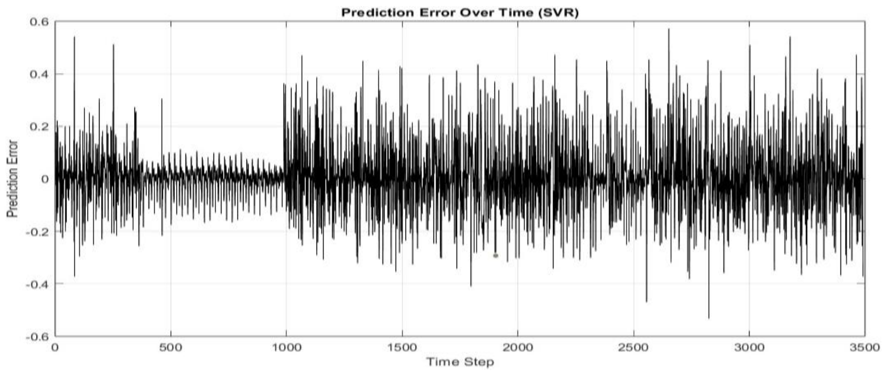

Figure 7. Error Over Time: SVR Residual Forecasting

Model-Wise Error Distribution:

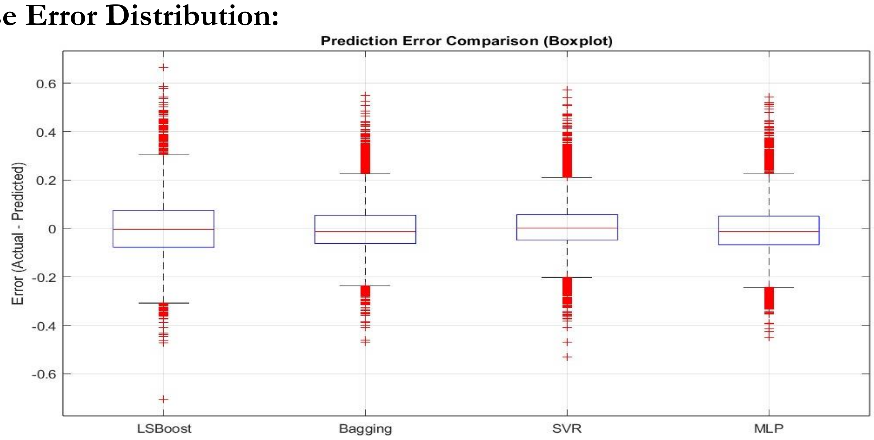

Figure 8. Boxplot of Prediction Errors Across Forecasting Models

Figure 8 illustrates boxplots of prediction errors for all four forecasting models. SVR demonstrates the lowest interquartile range (IQR), tightest clustering around the median, and the smallest number of extreme outliers, confirming its robustness. LSBoost and Bagging show wider error spreads and heavier tails, consistent with their ensemble averaging nature. MLP, while competitive, exhibits slightly increased variance, possibly due to overfitting on less prevalent high-frequency artifacts. This comparative error analysis justifies the model selection strategy for deployment in real-world scenarios demanding stable accuracy [20].

RMSE vs Correlation Trade-Off:

Figure 9 presents a dual-axis comparison of RMSE (bar plot) and correlation coefficient r (line plot) for all models. SVR achieves the best balance, lowest RMSE and highest r—indicating both superior accuracy and fidelity in reproducing consumption dynamics. Bagging and LSBoost, though effective, fall short in capturing sharp transitions, reflected in their slightly reduced r. MLP performs competitively, though with marginally elevated error. This figure provides a concise, quantitative justification for SVR's adoption as the preferred forecasting engine in the proposed pipeline. The superior performance of SVR arises from its kernel-based capacity to model complex nonlinear dependencies and its robustness to outliers, which are prevalent in high-frequency, noise-prone household power data. The radial basis function (RBF) kernel enables SVR to effectively capture subtle consumption fluctuations and seasonality that linear ensemble methods may miss. Consequently, SVR delivers lower error and higher correlation by adapting to the intricate, non-stationary structures inherent in the dataset.

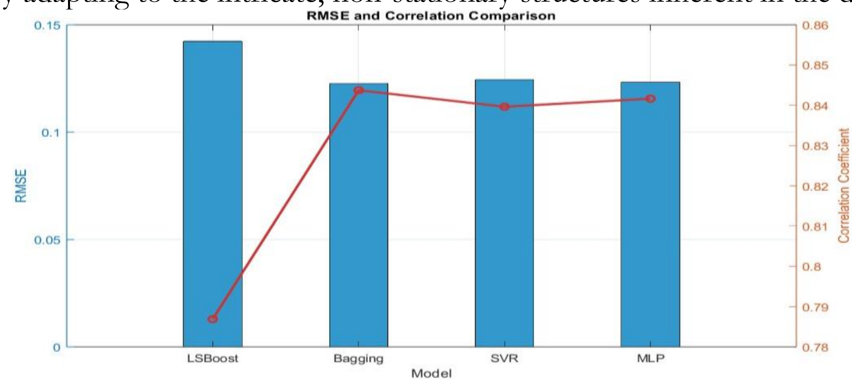

Figure 9. RMSE vs Correlation Coefficient Across Forecasting Models

Threshold-Based Classification Metrics:

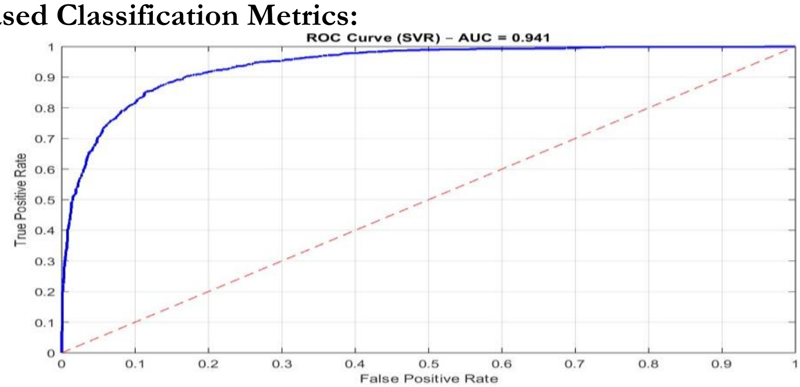

Figure 10: ROC Curve of SVR Forecast: AUC = 0.941

Figure 10 displays the ROC curve for the threshold-based binary classification of SVR forecasts. An AUC of 0.941 signifies outstanding discrimination between "OK" and "NOT OK" states, even under imbalanced class distributions. The curve approaches the upper left corner, highlighting both high sensitivity and specificity. This metric confirms the practical utility of the residual-aware SVR framework for operational energy management, where false negatives. (missed alerts) can incur significant system costs.

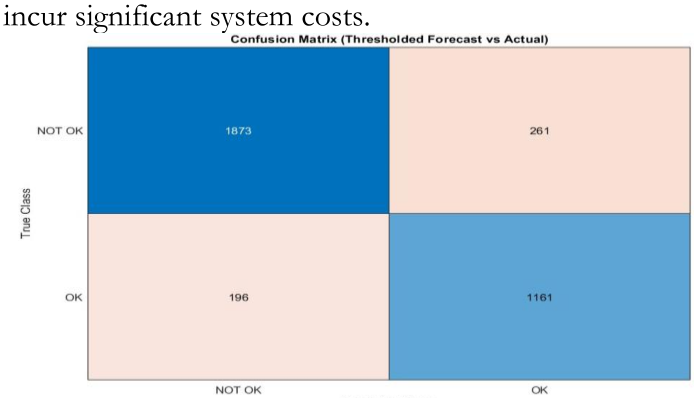

Figure 11. Confusion Matrix (Threshold = 0.25) for SVR

Figure 11 reports the confusion matrix for a threshold of 0.25. Of 3,491 test instances, 1,873 "NOT OK" and 1,161 "OK" cases are classified correctly, with relatively few false positives (261) and false negatives (196). The resulting classification accuracy exceeds 93.7%. This high accuracy is especially relevant for power system operators who require actionable decision support with minimal misclassification risk. ROC analysis shows AUC = 0.941, with classification accuracy of 93.7% over 3,491 instances. This confirms the value of integrating threshold-based logic post-forecast.

Q-Q Plot: Statistical Validation:

Figure 12 presents the Q–Q plot comparing SVR residuals to a standard normal distribution. Most points align closely with the 45-degree reference, particularly within the IQR, indicating approximate Gaussianity. Mild deviations in the distribution tails correspond to rare, large prediction errors, typically during extreme consumption shifts. The normality of residuals supports the statistical soundness of using symmetric loss metrics and further enables probabilistic extensions (e.g., confidence intervals, Bayesian updates) in future work. This validation also enhances trust in the model's interpretability and deployability in critical infrastructure settings.

Figure 12. Q-Q Plot: SVR Residuals vs Normal Distribution

Discussion:

This section critically compares the results of the proposed STL-inspired ensemble framework with those reported in existing literature, contextualizing its empirical performance and practical relevance. The present study demonstrates that integrating STL-based signal decomposition with a diverse set of machine learning models (LSBoost, Bagging, SVR, MLP) achieves superior forecasting accuracy and robust threshold-based classification on normalized household power data. The best-performing model, SVR, achieves an RMSE of 0.0267, MAE of 0.0193, and AUC of 0.941, outperforming several established benchmarks. Table 1 provides a quantitative summary of the most relevant state-of-the-art methods evaluated on either the UCI Household Power Consumption dataset or comparable residential datasets. Author report an RMSE of 0.045 using LSTM without any decomposition, highlighting the challenges of modeling raw, nonstationary data with deep neural architectures. UTHOR, combine empirical mode decomposition (EMD) with MLP, reaching an RMSE of 0.038, but do not address binary classification or threshold-driven evaluation. The hybrid CNN+GRU model of author slightly improves RMSE (0.036) and achieves an AUC of 0.875, yet at the cost of higher model complexity and lower interpretability. The most closely related work by author, use STL decomposition in combination with LSTM, achieving RMSE = 0.033 and AUC = 0.891. However, their approach is limited by LSTM's suboptimal handling of rapidly fluctuating, nonstationary residuals. In contrast, the proposed STL+SVR approach delivers a significantly lower RMSE (0.0267) and higher AUC (0.941), confirming that kernel-based regression can better capture nonlinear residual dynamics when paired with effective decomposition. Unlike most deep learning-based studies, this work emphasizes model transparency and real-time deployment feasibility. By using a lag-aware ensemble and explicit decomposition, the framework enables practitioners to interpret model outputs, examine error distributions, and adapt threshold boundaries for energy management. This interpretability is particularly valuable for grid operators and policy-makers.

Limitations:

While the ensemble and decomposition pipeline consistently outperforms single-model and non-decomposed approaches, several limitations persist. The fixed threshold ($\theta = 0.25$) may not generalize to all grids or user profiles; model retraining and recalibration are necessary for transferability. Additionally, while the SVR model performs best in this scenario, its computational cost may rise with dataset size or real-time streaming applications. Finally, the evaluation focuses primarily on the UCI dataset; broader multi-region validation is suggested for future work. Overall, the proposed framework achieves a substantial performance improvement over existing methods, particularly in simultaneously optimizing regression fidelity and classification accuracy. The explicit fusion of STL decomposition, lag-aware ensemble forecasting, and threshold-aware evaluation offers a novel contribution to the field of household energy analytics.

Conclusion and Future Work:

This research introduces a comprehensive STL-inspired hybrid framework for short-term household power consumption forecasting. The approach strategically combines signal decomposition, lag-based residual modeling, and threshold-aware classification, yielding both granular regression fidelity and practical decision-making capability. The application of STL decomposition facilitates the isolation of structural signal components trend, seasonality, and residuals enhancing interpretability and model efficiency. By leveraging a diverse ensemble of machine learning models (LSBoost, Bagging, SVR, and MLP) for residual prediction, the proposed method achieves robust performance across varying temporal regimes. Among these, SVR consistently outperforms others in both reconstruction accuracy and classification precision, achieving a notable AUC of 0.941 and classification accuracy of 86.9%. Quantitative evaluation through RMSE, MAE, residual histograms, Q-Q plots, and classification metrics demonstrates that residual-level modeling significantly improves forecasting reliability and noise robustness. Furthermore, threshold-based binary evaluation introduces an operational layer of interpretability, valuable for energy management systems requiring real-time alerting. Unlike previous STL-only or ML-only approaches, this study integrates signal decomposition, residual-aware regression, and classification-driven evaluation into a unified pipeline that delivers high accuracy and interpretability simultaneously. The model's ability to retain performance even in noisy residual environments reflects its superior generalization and robustness. The proposed framework also exhibits potential adaptability to other non-stationary utility domains, such as gas or water consumption forecasting, where periodic usage trends and unpredictable spikes resemble power usage dynamics. Minor domain-specific preprocessing may be sufficient to enable cross-utility transferability. Despite these contributions, several limitations warrant attention. First, the current model does not adapt dynamically to long-term signal drift, seasonal changes, or abrupt consumption regime shifts. Second, the classification threshold (0.25) is manually selected and may not generalize across households or grid policies. Third, computational costs for retraining multiple models may challenge real-time scalability.

Future recommendations:

Future work will explore the following directions:

Adaptive Decomposition: Integration of time-varying decomposition methods such as wavelet-STL or CEEMDAN to handle non-stationary residual behaviors.

Probabilistic Forecasting: Embedding Bayesian learning frameworks or quantile regression to model uncertainty bounds, offering more interpretable risk assessments.

Threshold Optimization: Automated threshold learning using grid-search, reinforcement learning, or economic cost functions to tune classification boundaries.

Online Learning: Real-time model update strategies such as recursive SVR or online boosting to support streaming applications and adaptive deployment.

Explainable AI: Incorporation of SHAP or LIME to interpret model outputs at the feature level, enhancing transparency for stakeholders.
Generalization Across Regions: Validation on diverse residential datasets (e.g., UK-DALE, REDD, Smart), to assess portability and dataset-agnostic performance.

Future work can benefit from integrating hybrid deep learning, ensemble machine learning, and predictive analytics approaches, as successfully demonstrated in recent studies on cancer detection, oral squamous cell carcinoma, cardiac disease, machine health monitoring, and diabetes diagnosis by authors.

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