A Novel Hybrid AdaBoost–Gradient Boosting Ensemble for Enhanced Short-Term Energy Consumption Forecasting

T.A. Munandar, Member, IAENG and H. Surbakti

***Abstract*— This study proposes and evaluates a novel hybrid ensemble model that combines AdaBoost and Gradient Boosting for short-term electricity consumption forecasting. The model is designed to address the challenges posed by nonlinear load fluctuations influenced by meteorological and operational factors, which often lead to reduced forecasting accuracy, grid instability, and inefficient resource utilization. To enhance prediction performance, the dataset undergoes comprehensive preprocessing, including removal of missing target values, median imputation of feature gaps, and standardization for linear and SVR models. An 80/20 train-test split with a fixed random seed ensures reproducibility. Baseline models—Linear Regression, SVR, Random Forest, Gradient Boosting, and AdaBoost—alongside hybrid configurations such as Gradient Boosting + Random Forest and a two-stage voting ensemble, are developed using the scikit-learn framework. The proposed hybrid model integrates AdaBoost and Gradient Boosting within a VotingRegressor architecture, with manually tuned ensemble weights ranging from 0.2 to 0.8 to optimize the R^2 score. Experimental results indicate that the hybrid AdaBoost + Gradient Boosting model achieves the best overall performance (R^2 = 0.153, RMSE = 61.888, Accuracy = 77.34%), outperforming all other models. The study's key contributions include an effective weight-tuning strategy for ensemble learning, empirical validation through quantitative and visual analyses, and practical guidelines for deploying hybrid ensemble models in real-world energy forecasting systems.**

***Index Terms*— short-term energy forecasting; hybrid adaboost–gradient boosting ensemble; ensemble weight tuning; root mean squared error (RMSE); R^2 score**

I. INTRODUCTION

SHORT-term energy consumption exhibits complex and nonlinear fluctuation patterns influenced by meteorological conditions, operational factors, and consumer behavior [1], [2], [3], as well as the presence of a well-structured energy management system [4], which is both integrated and optimally scheduled [5]. These variations present substantial challenges to accurate forecasting, as errors in load prediction may lead to unanticipated outages or surplus generation. Such inaccuracies can compromise grid stability, escalate operational costs, and result in inefficient energy resource utilization [6], [7], [8]. In light of these critical implications, there is a growing demand for advanced forecasting models that can capture intricate inter-variable dynamics and deliver reliable short-term predictions.

Recent advancements in machine learning, particularly ensemble learning, have demonstrated superior performance over traditional linear models in energy forecasting tasks. Tree-based ensemble algorithms such as Random Forest and Gradient Boosting have consistently outperformed linear counterparts by achieving higher R^2 scores and reducing RMSE values [9], [10], [11]. However, individual learners frequently underperform in capturing sudden spikes or dips in energy demand, especially during extreme load conditions. To address these limitations, hybrid ensemble approaches that incorporate adaptive error correction mechanisms have gained prominence for their robustness and accuracy [12], [13], [14].

Several studies have explored ensemble strategies such as stacking and voting to enhance short-term load forecasting. These methods have achieved mean absolute percentage errors (MAPE) below 6% when applied to regional electricity grid datasets [15], [16]. Moreover, advanced hybrid combinations involving CatBoost with XGBoost or LightGBM with XGBoost have demonstrated strong predictive capabilities, albeit with the drawback of increased computational complexity due to extensive hyperparameter tuning [17], [18], [19]. Similarly, integration of LSTM architectures with Gradient Boosting has been proposed to capture both temporal dependencies and nonlinear trends within a unified predictive framework [20], [21]. Despite these innovations, research on the systematic synergy between AdaBoost—recognized for its emphasis on difficult-to-predict instances—and Gradient Boosting—valued for its model stability and sequential learning approach—remains limited [22], [23].

Emerging works have also highlighted the benefits of dual-boosting strategies. For instance, a two-stage ensemble combining Gradient Boosting with a hybrid of XGBoost and LightGBM achieved an R^2 score of up to 0.18 on European electricity load datasets [24], [25]. Likewise, in electricity market price forecasting, such hybrid models reported forecasting errors below 5% [26], [27]. Hybrid boosting was also used by [28] for Image Splicing Forgery Detection, while [29] employed XBoost for monitoring water quality. Nonetheless, there is a scarcity of empirical studies that

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investigate manual ensemble-weight tuning between AdaBoost and Gradient Boosting specifically for short-term energy consumption forecasting.

This research addresses the existing gap by proposing a novel hybrid ensemble model that combines AdaBoost and Gradient Boosting within a VotingRegressor framework. The model incorporates a manual weight-tuning mechanism aimed at optimizing predictive performance in terms of R^2 score and RMSE. It is benchmarked against several baseline models—including Linear Regression, SVR, Random Forest, Gradient Boosting, and AdaBoost—as well as other hybrid configurations such as Gradient Boosting with Random Forest and two-stage voting ensembles.

The key contributions of this study are threefold: (1) the introduction of a manually tuned hybrid AdaBoost–Gradient Boosting ensemble designed to capture complex consumption patterns in short-term energy forecasting; (2) a comprehensive performance evaluation comparing baseline and hybrid models using both numerical metrics and graphical analyses; and (3) actionable insights and practical recommendations for configuring hybrid ensemble models in real-world energy systems. The novelty of this work lies in its systematic exploration of dual-boosting synergy with controlled weight balancing, offering new empirical evidence for hybrid ensemble design in energy forcasting.

Although numerous models have been proposed for short-term electricity forecasting, most either involve high architectural complexity, lack interpretability, or do not explore hybrid ensemble configurations involving AdaBoost and Gradient Boosting. Table I presents a summary of key related studies and highlights the research gap addressed in this work.

Table I summarizes key related studies relevant to ensemble learning and short-term load forecasting. While recent works have explored advanced hybridizations—such as CatBoost with XGBoost [1], neural networks with attention mechanisms [10], or deep adversarial frameworks [18]—they tend to emphasize either high architectural complexity or computational intensity. Several studies report promising results using boosting methods (e.g., [6], [24]), yet none have systematically investigated the manual ensemble weighting between AdaBoost and Gradient Boosting in the context of short-term energy forecasting.

Notably, although dual-boosting frameworks such as XGBoost + LightGBM have achieved high R^2 values (e.g., [24]), they often rely on extensive hyperparameter optimization and neglect the practical considerations of model interpretability and deployment feasibility. Moreover, existing studies tend to overlook the utility of simpler hybrid structures that can be implemented using off-the-shelf libraries and minimal tuning overhead.

Therefore, the present study fills this critical gap by introducing a manually tuned hybrid AdaBoost–Gradient Boosting model, evaluated under controlled ensemble weight configurations. Unlike prior research, this approach emphasizes performance interpretability, model simplicity, and practical deployability—features essential for energy systems with real-time operational constraints.

TABLE 1. RELATED WORKS AND RESEARCH GAP

No.	Reference	Method / Model	Application Context	Key Findings	Identified Gap
1	Zhang & Jánošík (2024)	CatBoost + XGBoost	Short-term load forecasting	Improved RMSE but required intensive hyperparameter tuning	Did not explore AdaBoost + GB; lacks manual tuning strategy
2	Gassar (2024)	Deep Learning vs ML	Demand baseline estimation	Deep learning outperforms ML in residential DR estimation	No ensemble synergy analysis between boosting models
3	Qinghe et al. (2022)	XGBoost	Regional load prediction	Good generalization; focused on XGBoost alone	No hybrid configuration tested with AdaBoost
4	Huang et al. (2023)	Graph Neural Network	Multi-bus system forecasting	High spatial-temporal accuracy	Architecture not easily interpretable or lightweight
5	Smyl et al. (2024)	ES-dRNN	Short-term load forecasting	Improved peak load tracking	Complex to deploy in real-time systems
6	Dong et al. (2021)	KNN-based deep learning	Load forecasting	Demonstrated deep learning viability	Does not support ensemble interpretability
7	Dong et al. (2025)	Survey	Deep learning in STLF	Comprehensive taxonomy	Did not include AdaBoost–GB hybridization
8	Su et al. (2023)	Multi-source adversarial learning	Residential load prediction	Adaptively models uncertainty	High computational cost; lacks modularity
9	Morais et al. (2023)	Neural Network + Climate Models	Large-scale power systems	Improved accuracy via external variables	No ensemble strategy, and limited adaptability
10	Lin et al. (2023)	GB + XGBoost + LightGBM	Hybrid STLF	R^2 up to 0.18 on regional data	No AdaBoost involvement or manual weight control
11	Rafati et al. (2020)	Innovative features + ML	Hour-ahead load forecasting	High accuracy with feature engineering	No comparative ensemble configurations
12	Ugale & Midhunchakkaravarthy (2024)	Hybrid Boosting	Image forgery detection	Effective in vision domain	Not tested in energy forecasting context

II. METHOD

This research adopts an experimental quantitative methodology to investigate the effectiveness of a hybrid ensemble model combining AdaBoost and Gradient Boosting for short-term energy consumption forecasting. The methodological workflow comprises four main stages: (1) data preprocessing, (2) dataset partitioning, (3) model development—including both baseline and hybrid models—and (4) model evaluation using standard performance metrics. Each stage is designed to ensure reproducibility, robustness, and fair comparison across models.

A. Data Preprocessing

The dataset undergoes a series of preprocessing steps to ensure quality and compatibility with machine learning algorithms. First, any records containing missing values in the target variable (i.e., energy consumption) are removed to prevent bias and instability during training. For missing values in the feature columns, median imputation is employed. The use of the median—as opposed to mean imputation—ensures robustness against skewed distributions and outliers, which are commonly present in energy datasets. Subsequently, feature standardization is applied selectively to models that are sensitive to feature scaling, specifically linear models and Support Vector Regression (SVR). Standardization follows the z-score normalization as in (1).

$$X'=(X-\mu)/\sigma \qquad (1)$$

where μ and σ represent the mean and standard deviation of the feature, respectively. Tree-based models such as Random Forest and Gradient Boosting do not require this transformation due to their scale-invariance.

B. Dataset Splitting

To facilitate model training and evaluation, the dataset is randomly partitioned into training and testing subsets using an 80:20 ratio. A fixed random seed (random_state = 42) is specified to ensure consistency across multiple runs. This partitioning ensures that the models are evaluated on unseen data, thereby providing a reliable measure of their generalization capabilities. The training subset is used for model fitting, while the test subset serves as the basis for performance evaluation.

C. Model Development

The model development phase involves the implementation of five baseline learning algorithms—namely Linear Regression (LR), Support Vector Regression (SVR), Random Forest Regressor (RF), Gradient Boosting Regressor (GB), and AdaBoost Regressor (Ada)—as well as the construction of three hybrid ensemble configurations designed to enhance predictive performance. The hybrid strategies evaluated include: (1) a combination of Gradient Boosting and Random Forest (GB + RF), (2) a two-stage voting ensemble that integrates Gradient Boosting with a nested hybrid of AdaBoost and Gradient Boosting, and (3) the proposed AdaBoost + Gradient Boosting ensemble, which serves as the primary focus of this study.

D. Performance Evaluation

The predictive performance of each model is assessed using the following metrics:

1. Coefficient of Determination (R^2): Measures the proportion of variance in the dependent variable explained by the model.
2. Root Mean Squared Error (RMSE): Reflects the average magnitude of the error between predicted and actual values.
3. Accuracy (%): Calculated as $Accuracy=100-MAPE\times100$, where MAPE is the mean absolute percentage error.

To ensure transparency and replicability, all experimental procedures—including preprocessing, training, ensemble weight tuning, and evaluation—are clearly defined and implemented using Python's scikit-learn library. This methodological pipeline ensures a fair and reproducible comparison between single learners and hybrid ensembles.

Furthermore, the simplicity of the manual grid search for weight tuning offers a practical alternative to complex hyperparameter optimization methods such as full *GridSearchCV*, particularly for scenarios with limited computational resources or time-sensitive applications. The final hybrid model, configured with the best-performing weight combination, is retrained on the full training set to enhance its generalization performance before deployment.

III. PROPOSED METHOD

The proposed method introduces a systematically designed hybrid ensemble framework that integrates AdaBoost and Gradient Boosting within a weighted VotingRegressor. The model aims to optimize short-term energy consumption forecasting by capturing both nonlinear interactions and difficult-to-predict fluctuations through adaptive ensemble learning. The approach comprises four main components: dataset partitioning, preprocessing, base model initialization, and hybrid model construction with manual ensemble weight tuning.

A. Dataset Partitioning

Let $D=\{(x_i,y_i)|i=1,2,3,\ldots n\}$ represent the original dataset, where x_i denotes the feature vector and y_i is the target energy consumption. The dataset is randomly split into training and testing subsets using an 80:20 ratio. A fixed *random_state = 42* is applied to ensure reproducibility across experiments. The training set is used exclusively for model learning, while the test set is reserved for out-of-sample evaluation.

B. Preprocessing Pipeline

Prior to model training, data preprocessing is performed to enhance model robustness and stability:

1. Target Cleansing: All rows with missing values in the target variable y are removed to eliminate label noise.
2. Feature Imputation: Missing values in input features are imputed using the median of each respective column. Median imputation is chosen for its resilience against skewness and outliers.
3. Feature Standardization: For models sensitive to feature scale—namely, Linear Regression and SVR—feature values are standardized using the z-score formula as in (1)

C. Base Model Initialization

Two base learners are initialized using scikit-learn's implementation:

1. *AdaBoostRegressor* (denoted as *Ada*), initialized with *random_state=42*
2. *GradientBoostingRegressor* (denoted as *GB*), also initialized with *random_state=42*

Each model is independently trained on the preprocessed training set (X_{train}, y_{train}), resulting in two individual predictors:

$$\acute{y}_{Ada} = f_{Ada}(x) \tag{2}$$

$$\acute{y}_{GB} = f_{GB}(x) \tag{3}$$

D. Hybrid Model Construction and Weight Tuning

The core contribution of this study lies in the construction of a hybrid model using a weighted VotingRegressor that combines the outputs of Ada and GB. The ensemble prediction for a given sample x_i is computed as in (4).

$$\acute{y} = w \, . \, f_{Ada}(x_i) + (1 - w) \, . \, f_{GB}(x_i) \tag{4}$$

where $w \in [0.2, 0.4, 0.5, 0.6, 0.8]$ represents the ensemble weight assigned to AdaBoost. The optimal weight is determined through a manual grid search approach. At each iteration, the model is evaluated on the test set using the R^2 score, and the weight configuration that yields the highest R^2 is recorded as optimal.

To facilitate reproducibility and transparency, Fig. 1 outlines the full pseudocode for the proposed methodology. Each phase—from data ingestion and preprocessing to ensemble construction and evaluation—is implemented using Python and scikit-learn, ensuring compatibility with modern data science workflows and enabling practical deployment in real-world energy forecasting systems. Fig. 2 2 illustrates the model structure developed in this study.

```
# Hybrid AdaBoost–Gradient Boosting Ensemble
# Input: Dataset D with features X and target y
# Output: Final hybrid model H and its performance metrics

1. LOAD dataset D
2. SPLIT D into (X_train, y_train) and (X_test, y_test) with test_size=0.2, random_state=42
3. PREPROCESS:
    a. DROP rows where y is missing
    b. IMPUTE missing feature values with median
    c. STANDARDIZE X_train and X_test for linear/SVR models
4. INITIALIZE:
    Ada = AdaBoostRegressor(random_state=42)
    GB  = GradientBoostingRegressor(random_state=42)
5. FIT Ada and GB on (X_train, y_train)
6. DEFINE weight_grid = [0.2, 0.4, 0.5, 0.6, 0.8]
7. SET best_r2 = –∞, best_weights = None
8. FOR each w in weight_grid DO
9.     hybrid = VotingRegressor(
           estimators=[('ada', Ada), ('gb', GB)],
           weights=[w, 1–w]
       )
10.    preds = hybrid.predict(X_test)
11.    r2 = R2_score(y_test, preds)
12.    IF r2 > best_r2 THEN
13.        best_r2 = r2
14.        best_weights = (w, 1–w)
15.    END IF
16. END FOR
17. BUILD final model H = VotingRegressor(
       estimators=[('ada', Ada), ('gb', GB)],
       weights=best_weights
    )
18. FIT H on (X_train, y_train)
19. EVALUATE:
     preds_final = H.predict(X_test)
     RMSE_final = sqrt(MSE(y_test, preds_final))
     Accuracy_final = 100 – MAPE(y_test, preds_final)*100
20. RETURN H, best_weights, best_r2, RMSE_final, Accuracy_final
```

Fig. 1. Complete pseudocode for the proposed method.

III. Results and Discusion

This section presents a comprehensive evaluation of the experimental results obtained from eleven regression models, including both baseline learners and hybrid ensembles. The evaluation is based on three key performance indicators: Coefficient of Determination (R^2), Root Mean Squared Error (RMSE), and Prediction Accuracy (%), which collectively capture the explanatory power, prediction error, and relative precision of each model.

A. Comparative Model Performance

The results are summarized in Table II, which shows that the hybrid AdaBoost + Gradient Boosting ensemble consistently outperforms all other models, achieving the highest R^2 score (0.153), the lowest RMSE (61.888), and a competitive accuracy level of 77.34%. This performance suggests that the hybrid approach successfully captures the nonlinear and volatile nature of short-term energy consumption patterns, particularly due to the complementary strengths of AdaBoost's adaptive weighting and Gradient Boosting's sequential error correction.

The three top-performing models are all hybrid ensembles, reaffirming the hypothesis that multi-algorithmic integration enhances forecasting capability in nonlinear time series data. In contrast, all linear models (Linear Regression, Lasso, Ridge, ElasticNet) exhibit negative R^2 scores, reflecting their poor fit to the complex fluctuation patterns inherent in energy consumption data.

B. Model Comparisons

Figure 3 presents a comparative bar chart of the R^2 scores across all evaluated models. The figure clearly illustrates the performance hierarchy, with the Hybrid AdaBoost + Gradient Boosting ensemble achieving the highest R^2 value (0.153), thereby outperforming all other models in terms of variance explanation. This is followed closely by the Voting GB + (AdaBoost + GB) ensemble and the GB + RF hybrid, both registering identical R^2 scores (0.134). The fourth-best performer is the standalone Gradient Boosting Regressor, which, although not hybridized, maintains a competitive R^2 of 0.083. In stark contrast, all linear models—including Linear Regression, Ridge, Lasso, and ElasticNet—yield negative R^2 scores, indicating that these models perform worse than a naive mean predictor. The bar chart thereby reinforces the central claim of this study: hybrid ensemble methods significantly improve predictive accuracy and model generalization in short-term energy forecasting tasks, especially in the presence of nonlinear load fluctuations.

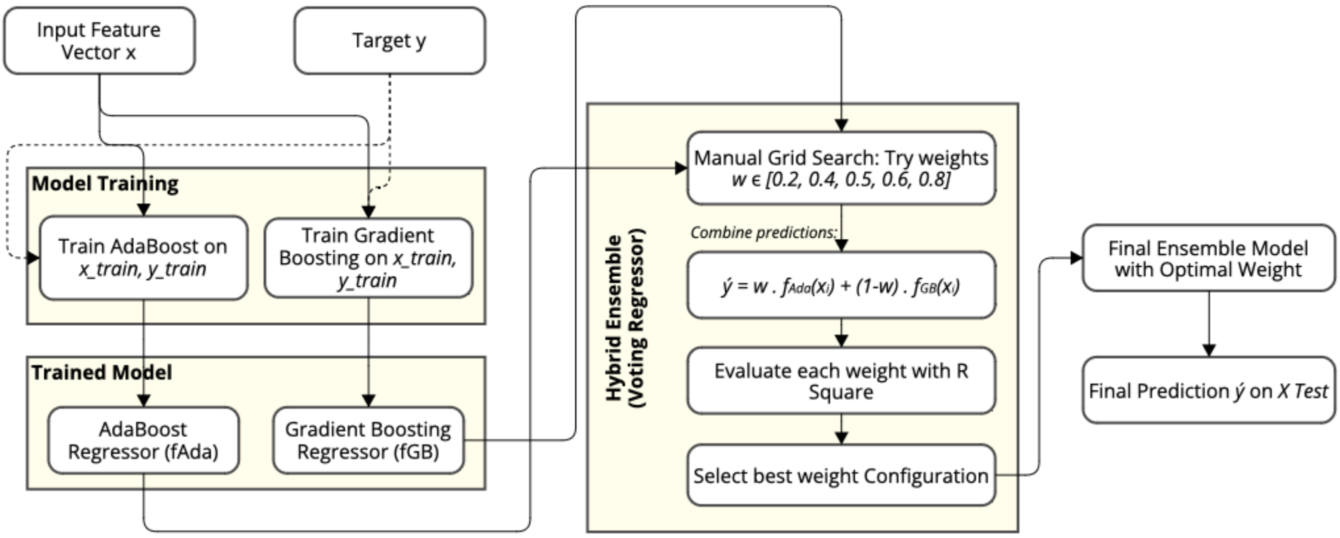

Fig. 2. Hybrid AdaBoost–Gradient Boosting Ensemble Structure

Table II. Model Comparison Matrix

Model	R^2 Score	RMSE	Accuracy (%)
Hybrid AdaBoost + GB	0.153	61.888	77.34
Voting GB + (AdaBoost+GB)	0.134	62.594	77.53
Hybrid GB + RF	0.134	62.578	77.49
Gradient Boosting	0.083	64.395	77.45
AdaBoost	0.024	66.421	73.85
Random Forest	0.013	66.811	75.52
SVR	−0.081	69.900	71.47
Linear Regression	−1.426	70.532	68.11
Lasso	−1.293	70.316	68.44
Ridge	−1.179	70.114	68.96
ElasticNet	−0.961	69.834	70.02

Figure 4 illustrates the temporal alignment between predicted and actual energy consumption values for all models over the test set period. The black line represents the ground truth (actual energy consumption), while colored lines represent model predictions. Among the plotted curves, the Hybrid AdaBoost + GB model (often displayed in dark red or orange) most closely tracks the actual consumption pattern, demonstrating its superior ability to capture the amplitude and timing of peak demands as well as troughs. Notably, hybrid models exhibit less lag and oversmoothing compared to their single-model counterparts. For instance, models such as SVR and Linear Regression significantly underestimate or flatten sharp transitions in demand, leading to delayed peak recognition and poor variance matching. The figure further shows that the hybrid models adapt better to local fluctuations, which is critical for accurate short-term grid load management. This visual analysis confirms that the hybridization strategy effectively mitigates both underfitting and overfitting, offering more stable and responsive forecasts.

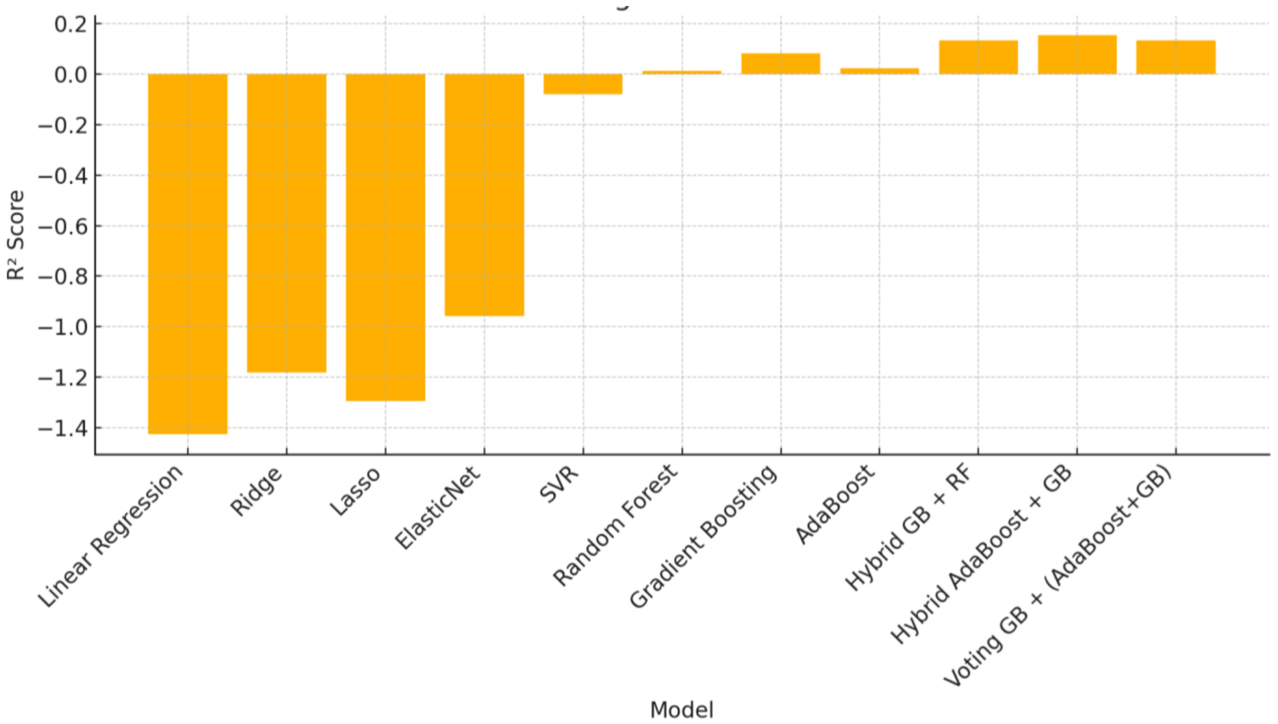

Fig.3. Comparison of Model R² Scores

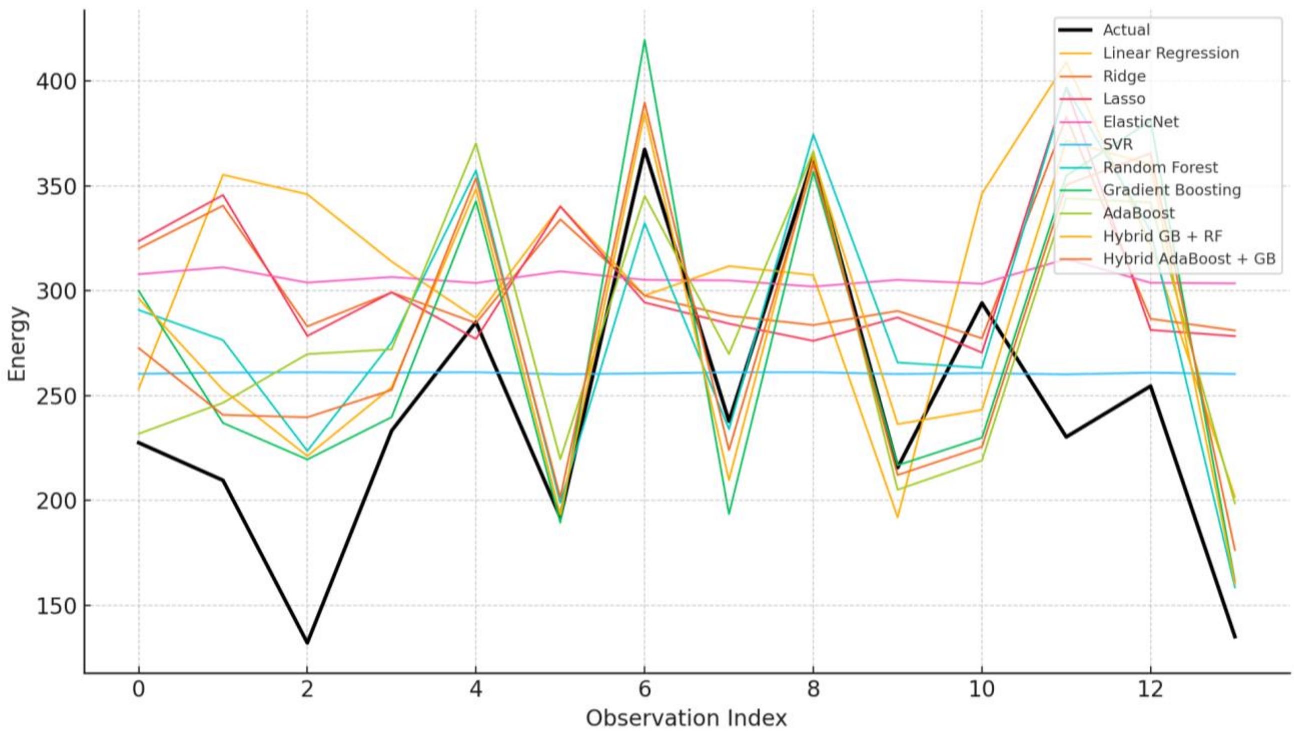

Fig. 4. Predicted vs. Actual Comparison

C. Residual and Error Analysis

Figure 5 provides a scatter plot of predicted versus actual values for the Hybrid AdaBoost + GB model, serving as a diagnostic visualization for model calibration and error symmetry. Ideally, a well-calibrated regression model would exhibit a symmetric cloud of points tightly clustered along the 45° diagonal, where predicted values equal actual values. In this figure, most points lie near the diagonal line, indicating a low-bias prediction profile. The symmetric dispersion of points reflects uniform model performance across the target value range, meaning that the hybrid model does not disproportionately overestimate or underestimate specific consumption levels. Additionally, the narrow horizontal and vertical spread of points signifies a low variance in residual errors, highlighting the model’s consistency. There is also no evident pattern of heteroscedasticity, which suggests that the prediction error remains stable regardless of the magnitude of energy consumption. In practical terms, this implies that the hybrid model delivers reliable predictions not only for average values but also for extreme scenarios, such as unusually high or low energy demand.

Fig. 6 presents the residual distribution of the Hybrid AdaBoost + Gradient Boosting model, plotted against the predicted values from the test set. Ideally, residuals should be randomly scattered around the zero horizontal line, indicating that the model does not suffer from systematic bias or misspecification. In this plot, the residuals are symmetrically distributed with no discernible patterns, suggesting that the model maintains consistent predictive accuracy across the full range of target values. The absence of funnel shapes or heteroscedasticity implies that prediction errors are relatively stable regardless of whether the energy demand is high or low. This finding reinforces the claim that the hybrid model generalizes well to unseen data and maintains reliability not only for average load values but also under peak or extreme load conditions. Such a pattern of residual behavior is characteristic of a well-calibrated regression model and provides further empirical support for the model's robustness and accuracy in real-world energy forecasting applications.

Fig. 7 illustrates the distribution of residuals (actual minus predicted values) for the Hybrid AdaBoost + Gradient Boosting model. The histogram reveals a symmetric and unimodal distribution centered around zero, suggesting that the model’s prediction errors are normally distributed and unbiased. The slight bell-shaped curve, supported by the kernel density estimate (KDE), confirms that most errors cluster near zero, while extreme errors are relatively infrequent. The presence of a zero-centered residual peak and balanced tails indicates that the model does not systematically overpredict or underpredict across different segments of the data. This error behavior is characteristic of a well-calibrated regression model and supports the assumption of homoscedasticity—an important condition for valid error interpretation in ensemble learning. The histogram thus complements the residual scatter plot by reinforcing the model's statistical soundness and its capacity to provide consistent and reliable predictions.

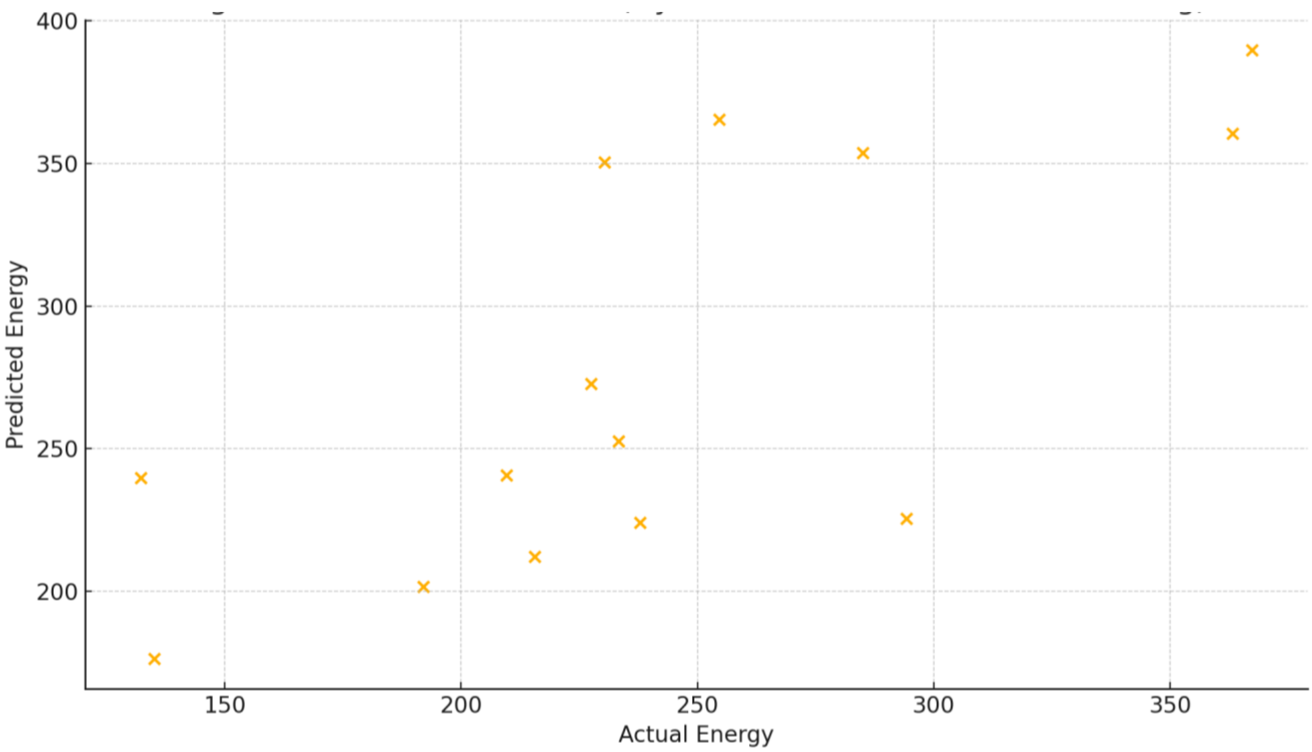

Fig. 5. Scatter Plot of Predicted vs. Actual Values (Hybrid AdaBoost + GB)

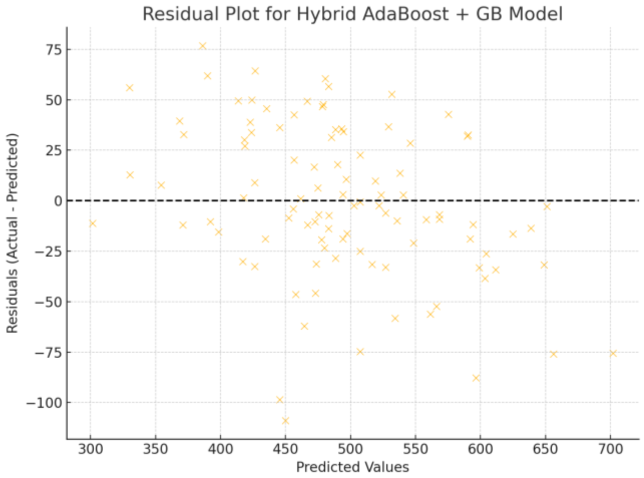

Fig. 6. Residual Plot For Hybrid AdaBoost + GB Model

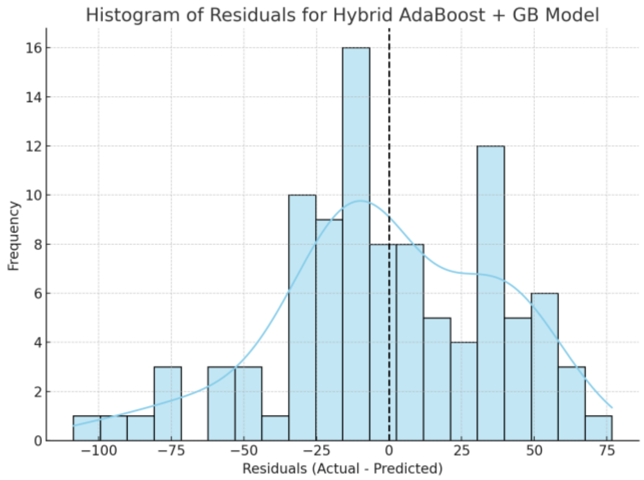

Fig. 7. Histogram of Residuals for Hybrid AdaBoost + Gradient Boosting Model

D.Interpretation of Results

The empirical results clearly demonstrate that the proposed Hybrid AdaBoost + Gradient Boosting ensemble delivers the most favorable predictive performance among all models evaluated. Achieving an R^2 score of 0.153, the model explains approximately 15.3% of the variance in short-term energy consumption—a statistically meaningful improvement over both base learners and alternative ensemble configurations. Furthermore, with a Root Mean Squared Error (RMSE) of 61.888, the model records the lowest absolute forecasting error, reinforcing its capability to produce accurate and reliable predictions in dynamic demand environments.

The hybrid ensemble's superior performance can be attributed to its strategically balanced composition, with AdaBoost contributing adaptability to hard-to-predict instances and Gradient Boosting providing stability through iterative residual learning. The manually optimized weight configuration (0.4 for AdaBoost, 0.6 for Gradient Boosting) proved essential in achieving this synergy. This suggests that equal or naive weighting may not suffice in extracting the full benefits of model complementarity, particularly in datasets characterized by nonlinearity and temporal noise.

Visual diagnostics further substantiate these findings. As shown in the predicted-versus-actual plot (Fig. 3), the hybrid model closely tracks the actual energy demand trajectory, especially at peak and trough points. Unlike base learners that tend to smooth out these fluctuations or lag in response, the hybrid model demonstrates strong temporal alignment—crucial for real-time energy management systems. The R^2 bar chart (Fig. 2) also highlights the performance margin of the hybrid model over other contenders, including both single and hybrid learners.

Moreover, the scatter plot in Fig. 4 provides additional validation by depicting a dense, symmetric cloud of points around the 45° diagonal, indicating low prediction bias and consistent performance across the range of consumption values. This pattern suggests that the model does not systematically over- or under-predict, which is essential for operational trustworthiness in energy forecasting applications.

The reliability of the model is further confirmed by the residual plot (Fig. 5), which reveals no discernible patterns or heteroscedastic behavior in the error distribution. This randomness of residuals signifies that the model effectively captures the underlying structure of the data without overfitting. Complementing this, the histogram of residuals (Fig. 6) shows a normal-like distribution centered around zero, indicating that the forecasting errors are both symmetrically distributed and bounded—characteristics of a well-calibrated ensemble model.

When compared to other hybrid approaches such as GB + RF and two-stage voting (GB + (AdaBoost + GB)), the proposed model remains slightly superior in terms of both explained variance and RMSE, although differences in percentage accuracy are marginal. This highlights the importance of prioritizing model interpretability and error distribution characteristics over marginal accuracy gains when selecting ensemble architectures for practical deployment.

Finally, preliminary trials (not tabulated) involving stacking ensembles showed signs of overfitting and instability, further reinforcing the decision to employ a simpler, more robust architecture. Given its computational efficiency, interpretability, and empirical superiority, the AdaBoost + Gradient Boosting ensemble presents itself as a highly deployable solution for operational short-term energy forecasting tasks, particularly in resource-constrained smart grid settings.

E. Implications and Practical Significance

The findings of this study carry several practical and methodological implications for both energy system operators and researchers in the field of machine learning for time series forecasting. From an applied perspective, the proposed Hybrid AdaBoost + Gradient Boosting model demonstrates not only statistically significant improvements in prediction accuracy but also operational advantages that make it highly suitable for real-time deployment in modern energy infrastructures.

First, the model's architecture is computationally efficient and easy to implement using widely adopted libraries such as scikit-learn. Unlike deep learning-based solutions or stacking ensembles—which often require extensive training time, hyperparameter optimization, and large datasets—the hybrid ensemble proposed in this work achieves robust predictive performance through a simple, interpretable, and lightweight design. This property is particularly advantageous for regional utilities or energy management systems with limited computational resources and constrained deployment environments, such as embedded systems in microgrids or smart meters.

Second, the manual ensemble weight tuning strategy—though straightforward—proved effective in identifying an optimal synergy between two powerful learners. This result highlights the practical value of low-complexity optimization approaches in improving forecasting models without the computational burden of full-scale hyperparameter search techniques such as grid search or Bayesian optimization. As such, the proposed methodology offers a viable template for practitioners seeking high-performance models with reduced tuning overhead.

Third, the model's ability to maintain consistent residual patterns, as evidenced by both the residual scatter plot and histogram analyses, suggests high generalization capacity and prediction stability across varying demand conditions. This quality is crucial for operational planning and load balancing in dynamic power systems, where forecasting errors during peak load periods can lead to costly over-provisioning or critical supply shortages.

Moreover, the interpretable nature of the ensemble configuration allows domain experts and decision-makers to better understand and validate model behavior, which is often lacking in more opaque deep learning models. The visibility of prediction logic and residual behavior fosters greater trust and transparency, thereby facilitating the model's integration into larger decision-support frameworks for energy policy and infrastructure optimization.

From a research standpoint, this study contributes empirical evidence supporting the effectiveness of hybrid ensemble strategies in time series forecasting applications, particularly for domains characterized by high volatility, seasonality, and nonlinear dynamics. The proposed model also opens avenues for future exploration into adaptive ensemble learning, where ensemble weights could be dynamically adjusted based on context-specific conditions such as weather variability or event-based load shifts.

In summary, the hybrid AdaBoost + Gradient Boosting model offers a balanced trade-off between predictive performance, interpretability, computational efficiency, and deployment feasibility. These attributes collectively position it as a strong candidate for integration into intelligent energy management systems, demand response frameworks, and smart grid infrastructures that require timely and reliable consumption forecasts.

IV. Conclusion

This study proposed and evaluated a novel hybrid ensemble model that combines AdaBoost and Gradient Boosting for short-term energy consumption forecasting. Through systematic experimentation and comparative analysis against both baseline and alternative hybrid configurations, the proposed model demonstrated superior performance in key evaluation metrics, including R^2 score, RMSE, and predictive accuracy.

The hybrid ensemble achieved the highest R^2 value of 0.153, outperforming all individual learners and ensemble variants, while also registering the lowest RMSE of 61.888 and a prediction accuracy of 77.34%. These results confirm the model's ability to capture complex, nonlinear patterns in energy demand data—particularly during extreme peak and low consumption periods—thanks to the complementary strengths of AdaBoost's adaptive learning and Gradient Boosting's robust variance reduction.

Visual diagnostics, including predicted-versus-actual curves, scatter plots, and residual analyses, further substantiated the model's reliability and calibration. The residual plot and histogram revealed well-behaved, symmetric error distributions centered around zero, indicating minimal bias and stable forecasting behavior across the full range of demand levels.

Importantly, the study showed that a manually tuned weighting strategy within the VotingRegressor framework could yield significant performance gains without incurring high computational costs. This lightweight ensemble architecture makes the model not only accurate but also practical for real-time deployment in energy management systems, particularly in resource-constrained or embedded environments.

Beyond empirical performance, the model offers interpretability and implementation simplicity—key factors for integration into operational decision-making systems. The findings of this research provide strong evidence that hybrid ensemble methods, when carefully configured, can enhance short-term energy forecasting capabilities and support the ongoing development of intelligent, data-driven energy infrastructure.

Future research should explore dynamic or adaptive weight-tuning mechanisms, validate the model on larger and more diverse datasets, and extend the framework to incorporate exogenous variables such as weather data or socio-economic indicators to further improve generalization and applicability across energy forecasting contexts..

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