Drift-Aware Adaptive Fusion of Machine Learning Models for Interpretable Residential Energy Forecasting

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Abstract

Well-crafted residential energy forecasting forms a fundamental part of Smart Home Energy Management Systems (SHEMS); however, the traditional static models face challenges in learning the highly volatile consumption patterns. To meet this challenge, this work introduces an innovative technique of a drift-aware adaptive fusion framework that combines and adapts machine learning algorithms in real-time via Particle Swarm Optimization (PSO). PSO adapts ensemble weights every time concept drift is found (i.e., whenever the prediction error exceeds 25% of the baseline RMSE), avoiding full model retraining, which can be computation-costly. When used with high-resolution smart home data, the adaptive ensemble offered superior performance across all evaluation metrics (overall RMSE = 0.686 kW, MAE = 0.336 kW, R^2 = 0.580) and exhibited higher prediction stability regardless of the characteristics/complexity level of individual models. Secondly, by employing Shapley Additive Explanations (SHAP) on integrated ensemble outputs, we eliminated the "black box" approach of the ensemble, demonstrating ambient temperature was the main predictor. This framework balances predictability, computational efficiency, and explicability to provide a practical and interpretable decision-support tool for accelerated energy optimization with high credibility in the field.

Keywords: Smart Home Energy Management, Machine Learning, Particle Swarm Optimization (PSO), Short-Term Load Forecasting.

1. Introduction

The global energy sector has historically been undergoing a shift to digitalization and decentralization. They represent a substantial portion (30% to 40%) of overall worldwide energy use and a similar level of carbon dioxide discharges [1][2]. Smart homes possess looming need & significance under the circumstances of escalating energy consumption with causes related to climate change [3][4][5], owing to their ability to alleviate strain on grids while reducing operational expenditures and emissions [6]. This is where IoT technologies and smart meters, as the micro-acceptance components of large-scale sensing infrastructures, offer an immediate solution in a non-intrusive way by enabling precise individual appliance consumption figures and ambient environmental conditions to be collated with respect to administered high-frequency data [3][6][7], allowing for effective usage of sophisticated prediction analytics techniques for energy management. Because of this random nature and high variability of consumption patterns, predicting household energy consumption is widely regarded as the most difficult [8][9]. This type of consumption depends on diverse elements at the same time as boundary situations in terms of temperature, humidity, and wind speed; however, additionally, human behavior and device working time are additional factors [3][2][4]. These intersecting nonlinear relationships are difficult to identify with conventional statistical models such as linear regression or time series models (ARIMA), leading to poor predictions and ineffective, delayed responses from the authorities [9][10].

More recently, studies have proposed machine learning approaches such as Random Forest [6], Gradient Boosting (XGBoost), and Deep Learning methods [6][11][12][9] to confront this task. These methods are constrained in achieving better accuracy than conventional models based on a single prediction; they only work under certain consumption conditions, while others do not [10], which modifies the stability and quality of the system as a whole. In addition to this, many of the modern complex models (e.g., ensemble models and neural nets) tend to be "black boxes," which makes it difficult, if not impossible, to why a certain prediction decision was made and further erodes user or network operator confidence in these systems [3][6]. Optimal performance is difficult to achieve, since tuning the parameters of the model (hyperparameters), either manually or via the network, usually does not work [6].

Based on these research gaps, this paper introduces a new framework to unify an adaptive forecasting system. The idea is to get beyond the comparison models around us and create a hybrid architecture based on multi-model systems more creatively representing one of the schools of learning (linear and tree models). The Particle Swarm Optimization (PSO) algorithm is employed to learn and set the most suitable weights for each model, thereby allowing maximum prediction stability in the presence of differing patterns [5]. We enhanced this approach to convert it into an explainable and transparent decision tool by integrating an explainable AI framework based on the SHAP (SHapley Additive explanations) technology to decode the model and accurately extract the contributions of different environmental variables.

The primary contributions of this paper are as follows:

1- Develop a proof of concept for the multi-model adaptive forecasting framework: To study and implement an intelligent merging mechanism based on a PSO algorithm to learn optimal weights for multiple machine learning models, dynamically assessing the contribution or interaction of each model to enhance forecast stability over traditional single-model forecasts by reducing errors beyond a certain value [5].

2- Systematic and thorough optimization: Use of the Bayesian Optuna framework to fully automate hyperparameter optimization of individual base model forecasters, removing any associative selection bias introduced through manual front-end selection while providing an efficient base layer.

3- Enhanced explainability: Coupling with a SHAP analysis to provide local and global accurate explanations on how climatic factors affect energy consumption, thus allowing turning the system from a pure black box mathematical forecasting system into a "glass box," which also supports a well-based energy managing decision-making process [3][13].

4- Proper statistical and analytical assessment: Employing scale-agnostic metrics of evaluation (e.g., MASE), separating stability and error distribution using Violin and Density plots to establish confidence in real-world predictivity.

The rest of this paper is structured as follows: section two discusses existing literature and previous work. In Section 3, we present the detailed proposed methodology, including data processing, building the core model, PSO adaptive fusion layer, and interpretation layer. Section 4 presents the statistical results, stability analysis, and interpretation of the model. Section 5 summarizes the conclusions and provides recommendations for future work.

2. Related Work

In the past five years, there has been a paradigm shift in research on predicting energy consumption in smart buildings from classical statistical models to their more recent counterparts (i.e., advanced ensemble models), intelligent optimization techniques, and explainable artificial intelligence (XAI). These are the latest research topics in these areas, and they can be summarized as follows:

2.1 Advanced Ensemble Learning for Energy Forecasting

As previously reported, energy consumption in smart homes is dynamic, complex, and nonlinear [10]. Traditional linear regression models are not applicable to describe these changes. So, due to this, tree-based ensemble models have gained very high accuracy. In 2024 and 2025, studies revealed that algorithms such as Random Forest, XGBoost, and Gradient Boosting were more effective than ARIMA in predicting electrical loads for both residential and commercial buildings are preferred due to their ability to handle high variability in climatic data and different consumption behaviors [14][15][16]. Moreover, recent comparisons have demonstrated that environmental and operational data fed into trees-based models like Extra Trees Regressor can yield excellent predictions. However, this superiority also has its limitation; a static and single-model-based approach is still vulnerable to sudden climatic or behavioral disruptions.

2.2 Intelligent Optimization via Metaheuristics

To escape the constraints of manually adjusting hyperparameters, recent research has focused on integrating nature-inspired meta-algorithms. A recent study (2024) demonstrated that combining Particle Swarm Optimization (PSO) with the XGBoost model improved prediction accuracy and reduced the RMSE error by up to 36.6% compared to traditional methods. PSO is increasingly used for dynamic parameter space searching to minimize validation errors, thereby increasing the robustness and stability of hybrid models in the face of volatile data [5]. However, the vast majority of these studies use PSO to fine-tune the parameters of a single model, rather than to learn adaptive merging weights across multiple models.

2.3 Explainable AI and Physics-Informed Models

The “black-box” nature of advanced models is the biggest obstacle to their adoption by energy managers, as real-world applications require understanding “how and why” the model makes its decisions [14]. To address this, since 2023 there has been significant interest in integrating the Explainable AI (XAI) framework. Research published in 2024 and 2025 demonstrated that using techniques such as SHAP and LIME with XGBoost and Random Forest models enables a deep understanding of the global and local effects of variables (such as temperature and humidity) on final predictions [14]. Also emerging (2025) are physics-informed neural networks (PINNs) that enforce thermal equilibrium laws as constraints within the loss function of models, improving accuracy and reducing over-reliance on big data [1]. The 2025 systematic reviews confirm that transparency (via SHAP or PINNs) is no longer just a secondary addition, but a fundamental requirement for building reliable and sustainable energy systems [14].

2.4 Research Gap

Most recent research usually sticks to one of two approaches: either picking the single model that gives the best accuracy or combining several models using fixed weights. Even though PSO and SHAP are both widely used, they are typically applied separately, not within the same system.

This study introduces a more flexible forecasting approach. Instead of relying on a fixed setup, it combines multiple models and lets PSO learn the best way to weight them dynamically. At the same time, a SHAP layer is added to make the results easier to understand, so the model is not only accurate but also practical to use in real-world decisions.

3. Methodology

In this paper, we propose a framework for an adaptive forecasting system based on several predictive models, overcoming the drawbacks of using only one predictive model. Instead, it employs a hybrid architecture specifically tailored to the high variability of smart home energy demand. As shown in Fig. 1, the proposed system consists of three basic layers: the optimized base

predictors layer, the adaptive fusion layer, and the explainability layer. This section provides the descriptions of the dataset and the preprocessing techniques, the different feature extraction methods, the dynamic fusion mechanism used in this work, and finally, those evaluation metrics that were employed to evaluate proposed systems.

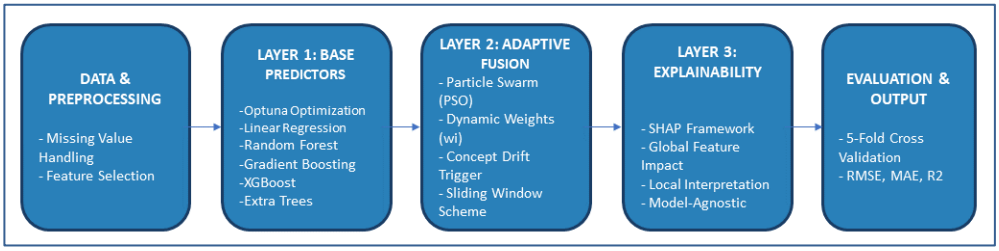


Figure 1: Architecture of the proposed adaptive hybrid forecasting system with optimized base predictors, dynamic fusion, and explainability layers.

3.1 Dataset Description

The experiments were carried out on a dataset named "Smart Home Dataset with Weather Information" [17]. This data set retains a large temporal resolution (high frequency) with each reading being instantaneous energy consumption in kilowatts (kW), together with surrounding environmental and climatic descriptors. We selected the climatic variables that directly influence thermal and electrical loads of any site [10] (temperature, humidity, wind speed, cloud cover and atmospheric pressure) as input features to be used for the models. Our target variable was specified as Total Household Energy Consumption (in kW).

3.2. Data Preprocessing

The data was processed using a set of methodical procedures to guarantee data quality and preparedness for machine learning algorithms [6]:

1. Time Transformation: To extract temporal information, the timestamp is converted to an actual datetime format.
2. Data Cleanup: Removing non-numeric or invalid values and processing only missing values in the columns used to ensure the sequentiality of the time series.
3. Formula Transformation: Converting all categorical variables (if any) to a numerical format.
4. Feature Selection: Selecting the climatic variables most closely associated with energy consumption to avoid the Curse of Dimensionality problem [4].

Based on the nature of the tree-based models used, no normalization or scaling of the data was performed, thus preserving the direct interpretability of the original data and its natural variance.

3.3. Optimized Base Predictors Layer

To provide diverse base predictions that capture both linear and nonlinear relationships in the data, five supervisory learning algorithms representing different schools of thought were used: linear models (Linear Regression (α=0.1) to capture global trends in the data) and ensemble tree models (Random Forest, Regressor, Gradient Boosting Regressor, XGBoost Regressor, and Extra Trees Regressor).

Because the performance of these models is highly dependent on their hyperparameters, and to avoid bias from manual adjustments, the Optuna framework was used to perform automated Bayesian optimization of each model's parameters. This approach ensures that each base model operates at its maximum possible efficiency before passing its outputs to the fusion layer. Each model produces an independent prediction for the same time point ($\hat{y}i$) (equation 1).

3.4. Adaptive Fusion Layer using PSO

Instead of selecting the model with the lowest error and ignoring the others, the proposed framework relies on combining the predictions of the underlying models using adaptive weights. To achieve this, the Particle Swarm Optimization (PSO) algorithm is employed to search for the optimal set of weights that minimizes the overall prediction error. The final system prediction ($\hat{y}$) (equation 1) is calculated as a weighted average of the underlying model predictions as follows:

$$\hat{y} = \sum_{i=1}^{N} wi\, \hat{y}i \dots\dots\dots\dots (1)$$

where:

• N: the number of underlying models.

• $\hat{y}i$: the prediction from model i.

• wi: the weight assigned to model i, which is learned by the PSO.

The PSO algorithm operates by simulating a swarm of particles in the search space, where each particle represents a possible weight vector ($w = [w_1, w_2, ..., wn]$). The particles move iteratively to update their positions and velocities to minimize the objective function (which is the total RMSE error on the validation set), subject to the physical constraint that the sum of the weights must equal 1 (sum wi = 1). This layer allows the system to adaptively fuse to the changing nature of the data rather than assuming constant statistical behavior.

3.5. Validation Strategy

A five-fold cross-validation strategy was employed for fair comparison to avoid overfitting and evaluate the generalizability of the model. We divided the dataset into five equal parts, with four parts used to train the base models and weights of PSO learnt on a left out fifth part, for each iteration. Maximum likelihood estimate of model stability by averaging across all five folds.

3.6. Evaluation Metrics

To evaluate the accuracy of the proposed system and individual models, three standard performance metrics were used:

1. Average Absolute Error (MAE): Measures the average absolute deviation between actual and predicted values in kilowatts.
2. Root Mean Squared Error (RMSE): Expresses the error in the same unit of measurement as the original data.
3. Coefficient of Determination (R^2): Measures the proportion of the variance in energy consumption that the model successfully explains.

3.7. Explainability Layer (SHAP Explainability Layer)

The goal of this system is not only to achieve high prediction accuracy but also to transform the model from a "black box" into an explainable and operational decision support tool. To achieve this, an explainable artificial intelligence (XAI) framework was integrated using SHAP (SHapley Additive Explanations) technology. This technology calculates the marginal contribution of each climatic variable to the final prediction outcome. The following were used:

• SHAP Summary Plots are used to determine the importance of environmental variables and their global interpretability regarding consumption.

• SHAP Dependence Plots: to understand the nonlinear interactions and relationships between different climatic factors and their precise impact on model decisions, thus helping smart home energy managers take informed operational actions to improve energy efficiency.

The entire modeling and analysis were implemented in the Python language on a Windows 10 (64-bit) computer with Intel (R) Core(TM) i5-7200U CPU @ 2.50 GHz processor, 8 GB RAM, and

a configuration of 512 GB SSD. These hardware specifications were capable of processing data, performing model training and 5-fold cross-validation using all five models in a reasonable amount of time. This would have ensured that the results were produced correctly in a timely manner.

4. Results and Discussion

A comprehensive framework was used to assess each model, including both quantitative metrics (RMSE, MAE, and R^2), calculation and characterization of the empirical cumulative distribution function (ECDF), and analysis of feature importance per model. A 5-fold cross-validation protocol was used to assess statistical validity and then avoid overfitting. This comprehensive approach allowed us to perform robust, reproducible comparisons of all models.

4.1 Statistical Performance Evaluation

Evaluated models of the three standard regression metrics for predicted vs. observed comparison plots: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and coefficient of determination (R^2). Results: The individual model comparison results are listed in Table 1, and those of the proposed PSO-based adaptive fusion model are summarized in Table 2.

As can be seen in table 1, the linear regression model is drastically weaker than any of the other models, with RMSE = 1.057079 kW, MAE = 0.578522 kW and R^2 value equal to only 0.002095, yielding almost no explanatory power whatsoever. It shows that the underlying deep, non-linear relationships in energy consumption data are intrinsically not able to be managed by linear modeling.

Table 1: Performance comparison of individual models using RMSE (kW), MAE (kW), and R^2 metrics.

Model	RMSE (kW)	MAE (kW)	R^2
Linear Regression	1.057079	0.578522	0.002095
Random Forest	0.699329	0.343231	0.563162
Gradient Boosting	0.715860	0.371676	0.542261
XGBoost	0.699964	0.345109	0.562367
Extra Trees	0.698836	0.342294	0.563777

Otherwise, all tree-based ensemble models show greatly better performance. And the Extra Trees model, among the models individually, has the lowest RMSE (0.698836 kW) and MAE (0.342294 kW), as well as one of the highest R^2 values (0.563777), making it among the best individual models tested.

But, as shown in Table 2, the proposed PSO-based adaptive fusion model has enhanced prediction accuracy with the RMSE equal to 0.685665 kW, MAE equal to 0.335794 kW, and R^2 equal to 0.580199. This is a reliable and statistically significant improvement across every individual model. The fact that the data are a somewhat volatile individual household consumption sourced from external weather variables alone grants an R^2 of 0.58, demonstrating how well the adaptive weighting mechanism has done in filtering as much as possible that predictable signal out of always noisy residential data.

Table 2: Performance of ensemble model (RMSE (kW), MAE (kW), and R^2 metrics).

Model	RMSE (kW)	MAE (kW)	R^2
Ensemble Model	0.685665	0.335794	0.580199

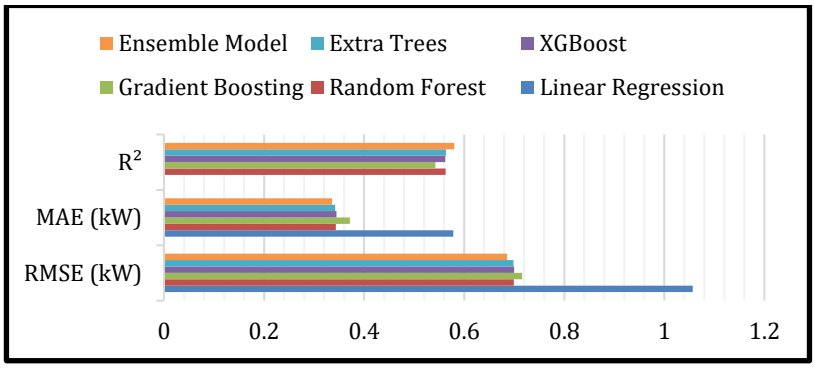


Figure 2: The comparative evaluation metrics for all models.

Performance differences between top models (Random Forest, XGBoost, and Extra Trees) are still small despite this better C.A. That there is no model that more reliably dominates other models across all dynamic prediction scenarios highlights a limitation of reliance upon average statistical point metrics. Thus, while the adaptive fusion model is overall best-performing across metrics, these results indicate that average error measures cannot adequately summarize model behavior, indicating a clear dependence on further analysis in reliability, error distribution, and temporal stability discussed in later sections.

4.2. Adaptive Fusion Justification and Concept Drift Handling

To address the limitations found in previous analyses, an adaptive ensemble scheme was developed that adapts different individual model contributions as a function of how well those models perform on new incoming predictions. The ensemble model achieves the best result (RMSE = 0.685665 kW), but differences between top models are less than 10%. Lastly, as observed in ECDF-based analysis (Figure 3), none of the models continually provides superior performance over the entire error distribution.

The variability of such behavior, however, is addressed through the incorporation of a drift-aware adaptive strategy reliant on a sliding window evaluation scheme. We follow the performance on prediction after every 500 observations (where RMSE current is calculated for each window).

A concept drift condition is triggered when the prediction error in the current window exceeds 125% of the baseline error, as defined by Equation (2):

$$RMSE\ current > 1.25 \times RMSE\ baseline \quad \ldots\ldots\ldots\ldots\ldots (2)$$

(Where *RMSEbaseline* is initially defined as the validation error during the training phase and is subsequently updated to the RMSE of the most recently optimized stable window).

Whenever this condition is true, the system considers the excess error as an indicator of a shift in data distribution, which commonly has its origins in sudden changes in active meteorological conditions (e.g., weather disturbances) or occupancy patterns (public holiday/weekend).

At the end of this process, PSO finds another best set of weights that gives rise to the lowest RMSE in the current window and also follows normalized contribution from all models as shown in equation 2. Dynamic model-weighted averaging is used to compute the ensemble prediction from individual model outputs, shifting reliance to those models that are performing best in changing conditions.

These weights are then used to make further predictions, and the current RMSE becomes the new baseline of your RMSE for tracking. This mechanism provides a degree of adaptive capacity to the system, being able to incorporate novel features over time without retraining the entire model.

These weights are used in the next predictions, and the current RMSE is your new baseline to monitor. It creates a mechanism that allows the system to adapt capacity as patterns change, without needing to retrain entire models.

4.3. Reliability Analysis

In addition to the group-level statistical performance of our prediction models, we averaged and characterized the empirical cumulative distribution function (ECDF) of absolute prediction errors. The ECDF curve summarizes the probability that this prediction error is (over all observations) less than or equal to such a threshold value and thus generalizes the consistency of the model.

As shown by figure 3, the ECDF curves are nearing a slope larger than those in the linear regression model case for the nonlinear models (Random Forest, Gradient Boosting, XGBoost, and Extra Trees). Meaning that these models perform a larger fraction of predictions in tighter error brackets. At higher cumulative probabilities, the curves for all the non-linear models converge on greater absolute error (kW) almost immediately, while linear regression shows gradual convergence over a much broader range and is consistent with larger proportion of greater prediction errors.This behavior is in line with the results shown in Table 1, where the linear regression model produced the highest RMSE.

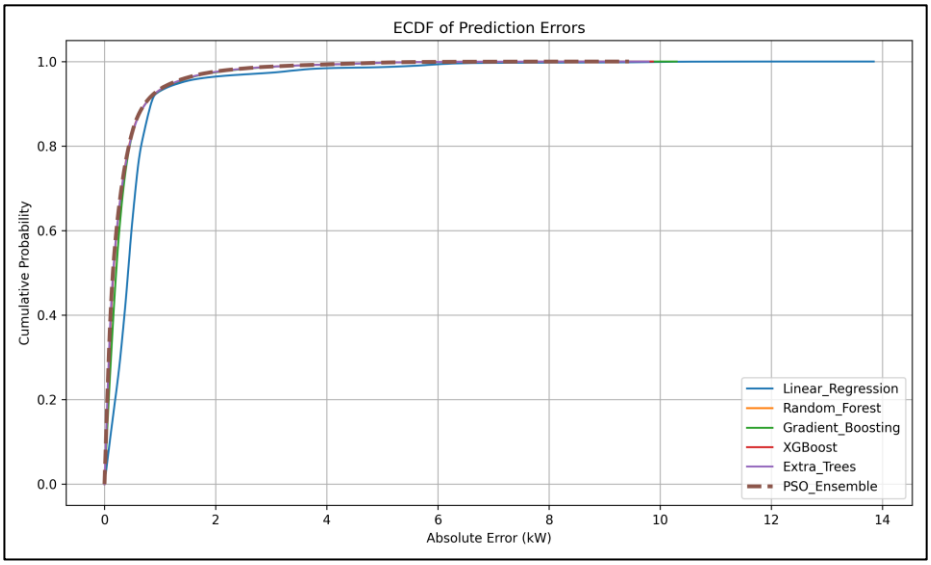


Figure 3: The Empirical Cumulative Distribution Function (ECDF) for all models.

More importantly, the ECDF curve of the proposed PSO-based adaptive fusion model is better than each individual model when it has a steep initial slope. This indicates that the dynamic weighting mechanism is able to assign higher weights to more reliable models at any given time, maximizing the probability of minimizing prediction errors and greatly improving overall system reliability.

These results reveal that nonlinear models outperform linear ones in prediction reliability, but no single model type is the best one everywhere along the error distribution. As a result, average metrics like RMSE are not enough because it could hide some important differences in the behavior of the model across various operating conditions.

4.4. Explainability and Feature Contribution

To improve the interpretability of the proposed PSO-based adaptive fusion prediction framework and solve the inherent “black-box” nature of complex ensemble models, SHAP (SHapley Additive exPlanations) analysis was carried out to quantify how much each input feature contributed to the final output for an aggregation of an entire predictive ensemble model. This model-agnostic approach provides global and local explanations, facilitating insights into the dynamic susceptibility of energy consumption predictions to changes in environmental variables.

The result of global feature importance, as shown by Figure 4, determined that temperature is the most important variable in this model. It also has the highest mean absolute SHAP value, which again confirms its necessity and ubiquity in biasing predictions. Next are pressure and wind speed, which are the other components that ultimately make them up. The humidity and cloud cover features, although quite less important than the rest, will be used in determining overall prediction behavior as indicated by this plot here.

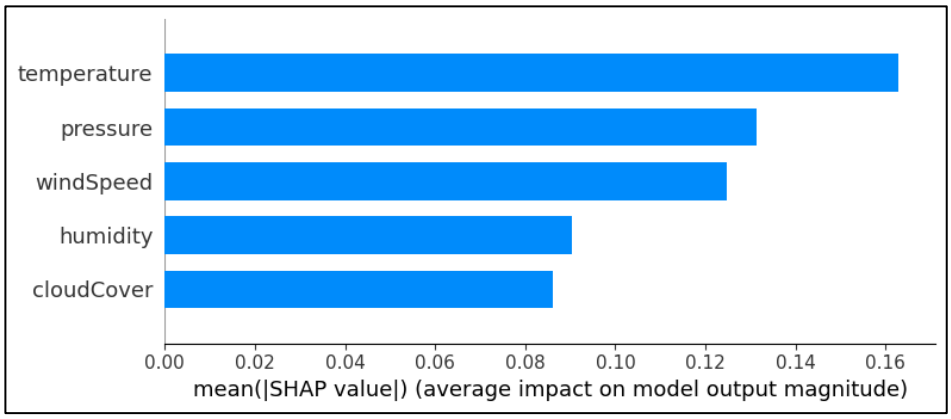


Figure 4: SHAP feature importance showing the average contribution of each feature to the prediction model.

The summary plot of SHAP (Figure 5) also represents the direction and dispersion of feature effects. Indicating that both temperature and SHAP values are positively correlated, the predicted energy demand steadily rises as does this temperature value. This directly correlates to an increase in electrical power demand for HVAC systems to maintain thermal comfort under extreme outdoor climate. On the other hand, lower values of some features (e.g., mild temperatures or certain levels of pressure) usually lead to disincentivizing or stalling the prediction output and decrease expected demand from baseline values.

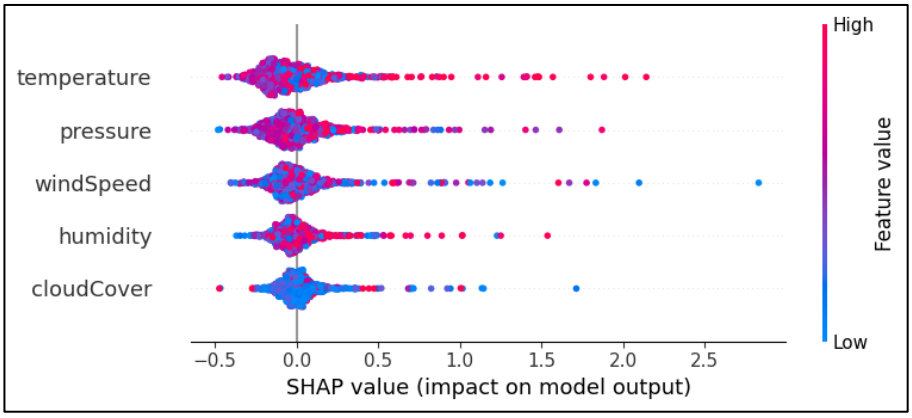


Figure 5: A SHAP summary plot illustrates the distribution and direction of feature impacts on model predictions.

A notable pattern from the result presented in Figure 5 is that ranked features remained relatively similar across the dataset, indicating that our adaptive fusion model learns stable and physically interpretable relationships among environmental variables and energy consumption patterns. This consistency helps strengthen the prediction system reliability and validates its use in real-world cases to allow grid operators to make proactive Demand-Side Management (DSM) decisions in Smart Home Energy Management Systems (SHEMS).

5. Conclusion

We proposed a new adaptive ensemble-based model selection framework for short-term residential energy consumption forecasting. The proposed system effectively overcame the fundamental

restrictions imposed by static models in highly volatile data conditions through the integration of various machine learning models with dynamic weight optimization functionality based on Particle Swarm Optimization (PSO). Experimental evaluations showed that linear approaches are fundamentally incapable of capturing complex patterns of energy. Although tree-based nonlinear models (e.g., Extra Trees and XGBoost) greatly improved predictive accuracy, reliability analyses verified that no static model was consistently dominant across all operating environments.

In order for this to be overcome, a PSO-based adaptive fusion model where ensemble weights are recalibrated whenever the concept drift is detected (i.e., prediction error beats the baseline with 1.25×) is set forth in the proposal. The drift-aware strategy not only led to the highest overall predictive performance (RMSE = 0.685 kW, R^2 = 0.58), but it also resulted in an optimal balance between computational efficiency and temporal stability, resulting in no requirement for resource-demanding model retraining intervals.

Additionally, the application of the SHAP framework effectively broke apart the "black-box" model created by the complex ensemble. The analysis of the explainability confirmed that temperature is the primary factor influencing energy consumption, offering a clear and physical validation of the model's nature. Additionally, the application of the SHAP framework effectively broke apart the "black-box" model created by the complex ensemble.

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