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A Statistical Modelling Framework with Adaptive Multi-Model Switching for Short-Term Load Forecasting

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ABSTRACT

Short-term load forecasting (STLF) is still an essential operational necessity in today's electric power system, especially in relation to the increasing variability in electric demand, renewable energy integration, and development of smart grid infrastructure. The application of statistical techniques and machine learning algorithms in STLF has been highly promising. However, most of the techniques used in STLF have been based on fixed model or ensemble strategies that do not account for input-dependent variations in electric demand. Such inflexibility in dealing with electric demand is likely to limit their effectiveness in dealing with non-linear, non-stationary, and peak demand conditions. To fill in this knowledge gap, this paper proposes an adaptive statistical modelling approach with multi-model switching for short-term electric load forecasting. The proposed approach combines seven state-of-the-art models, namely linear regression, ridge regression, Lasso regression, Support Vector Regression (SVR), Random Forest, CatBoost, and LightGBM. Furthermore, it proposes an adaptive switching approach that combines model predictions using instance-level model performance. The proposed approach is tested using hourly electric demand data from the New York Independent System Operator (NYISO) dataset. A comprehensive set of preprocessing techniques, including normalization, outlier handling, and feature development, is also used. The experimental results validate that the proposed approach performs better than existing techniques with an accuracy increase of 3-5%. Moreover, the proposed approach also shows improved performance in terms of reduced root mean squared error. Furthermore, statistical validation is also used to confirm the effectiveness of the proposed approach

Keywords: Adaptive Switching Mechanism, Autoregressive Integrated Moving Average (ARIMA), Categorical Boosting (CatBoost), Gradient Boosting Machine (GBM), Short-Term Load Forecasting (STLF)

I. INTRODUCTION

Short-term load forecasting (STLF) is an essential tool for accurate prediction in complex and uncertain environments, which is expected to increase in the future with the development of complex power systems. The increasing use of renewable energy sources, demand-side variability, and distributed generation has significantly altered the characteristics of electricity consumption patterns [1], [2], [3], [4]. It is expected that in such environments, the forecasting models should not only offer accurate prediction of the load, but they should also be able to maintain stability in uncertain environments. Recent machine learning-based models have shown their effectiveness in accurately modelling the non-linear relationships of load demand, which can offer better performance compared to conventional statistical models [5]. For instance, machine learning models have shown significant potential in accurately capturing the temporal relationships of load demand, which is difficult to achieve using conventional models, highlighting the capability of recurrent neural networks and LSTM models for complex time-series prediction [6],[7],[8]. Deep learning models, along hybrid models, have shown their success in solving industrial-scale forecasting problems, which can offer better accuracy in uncertain environments [9],[10],[11].

Parallel to this, there have been improvements in deep learning-based methods, where better performance can be achieved through hierarchical feature extraction [12], [13]. In addition, studies that compare different neural network architectures highlight the effectiveness of these models, especially for short-term forecasting problems, where temporal dependencies are considered [14]. Another area that has gained significant attention in the field of load forecasting is ensemble-based models, where different learning paradigms are combined. Based on the data they have [15], these models can learn different patterns. Advanced learning strategies and optimization techniques are considered effective for achieving superior outcomes [16],[17]. As a result of Gradient boosting-based models and hybrid ensemble-based models, both linear and nonlinear patterns can be acquired from load data [18]. However, most current models rely on static combination strategies.

This observation highlights a significant research gap. Although a few models are typically used, the

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combination of predictions does not consider input-specific variations in model performance [19]. Sometimes, one model performs best when demand peaks, while another shines when demand is stable or low variability. Forecasting may suffer from a fixed combination strategy, since it cannot adapt to these changes. To address this problem, our paper introduces a multi-model switching mechanism within a statistical framework. To test this, we used hourly load data from the New York Independent System Operator [20], which shows real-world fluctuations in load. Our performance gains aren't skewed by specific data when we use a standard dataset.

In addition to contributing to performance, our work also contributes to practical performance applications. We developed a multi-model statistical forecasting structure that includes different baseline models suited to different characteristics of load data. Furthermore, we propose a switching mechanism for instance-level prediction selection, which enables the system to choose the most fitting forecasts. To make good use of the load data, we also built a structured preprocessing and feature engineering pipeline. A thorough evaluation is completed, including error analysis and robustness tests.

The rest of the paper follows in this order. Section II introduces the methodological framework, which includes data preprocessing, the model construction, and the proposed switching strategy. In Section III, experimental results and analysis are discussed.

II. METHODOLOGY

The problem of short-term load forecasting is defined as a supervised regression problem, in which past observations and calculated features are used to predict future electricity demands. In other words, if we are given an input feature vector of system conditions at time step, we can predict the load value in the next time step. This definition of the problem is suitable for using machine learning models to learn the relationship between past observations and future demand values.

A. Data Source and Preparation

The data set that was used in this research comprises the values of the electricity demand at every hour. The data was collected from the New York Independent System Operator [20]. The data set has the advantage of providing precise time resolution and represents the real-world variations in the data. Before training the models, several operations are carried out on the data. The data is cleaned by removing the missing values. The missing values are filled using interpolation methods. The data is also cleaned by removing the outliers. The outliers are identified based on the statistical values. In order to avoid distortions during the training, outliers are removed. For linear and kernel models, feature scaling is performed.

B. Feature Engineering

Furthermore, feature construction is crucial for capturing temporal dependencies and variations in the load data. Temporal features include hours of the day, days of the week, and months of the year. Lagged features: Load values at 1-hour, 6-hour, 12-hour, and 24-hour intervals. There are two types of rolling features: rolling averages and variances. There are two types of event features: holiday indicators and special event indicators. These features allow the model to capture both the short-term variations and the long-term periodic variations in the data, as emphasized in the recent studies on load forecasting [1],[2].

C. Baseline Models

A total of seven baseline models is used to produce the predictive output, including Linear Regression, Ridge Regression, Lasso Regression, Support Vector Regression (SVR), Random Forest, CatBoost, and LightGBM. The models selected cover a wide variety of machine learning paradigms, including linear models, regularized regression models, kernel methods, and ensemble tree-based models. The use of such heterogeneous models enables the framework to handle various data characteristics, from linear to complex non-linear data. Past research has suggested that by harnessing the power of multiple models, the accuracy of the forecasting can be improved, as in the case of dynamic environments such as short-term load forecasting.

D. Adaptive Multi-Model Switching Mechanism

The main component of the suggested framework is the adaptive switching mechanism, which controls the use of the predictions made by different baseline models. Unlike traditional ensemble methods, which use fixed weight calculations, the suggested method analyses the output of all the baseline models and makes the final prediction based on the relative behavior of the output of each input instance. To be more precise, the predictions made by all the models are collected and analyzed in terms of their values and consistency for each input instance. Then, the predictions are ranked and a subset of the most reliable predictions is selected. The final prediction is made by aggregating the predictions in the selected subset, ensuring that only the most relevant information is used in the output. This makes the suggested framework more adaptive and effective in different data scenarios by leveraging the best of each model in different scenarios. Unlike traditional ensemble methods, the suggested method is based on the switching mechanism, which operates at the instance level, making it more flexible and adaptive. To address this limitation, adaptive multi-model

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switching mechanisms dynamically select the most suitable forecasting model based on the prevailing characteristics of the input data rather than relying on a fixed prediction strategy.

Algorithm:

Algorithm 1: Adaptive Multi-Model Switching for Short-Term Load Forecasting
Input:
  Historical load dataset D
Output:
  Final predicted load values $\hat{y}$
1. Load dataset D
2. Perform data preprocessing:
   - Handle missing values
   - Remove outliers
   - Apply normalization (if required)
3. Perform feature engineering:
   - Extract time features (hour, day of week)
   - Generate lag features (1, 6, 12, 24 hours)
   - Compute rolling statistics (mean, standard deviation)
4. Split dataset into training set and testing set
5. Train baseline models:
   - Linear Regression
   - Ridge Regression
   - Lasso Regression
   - Support Vector Regression (SVR)
   - Random Forest
   - CatBoost
   - LightGBM
6. Generate predictions from all models:
   $P = \{P_1, P_2, P_3, ..., P_7\}$
7. Apply adaptive switching mechanism:
   For each test sample i:
     a. Collect predictions $\{P_1(i), P_2(i), ..., P_7(i)\}$
     b. Sort predictions in ascending order
     c. Select top-k highest predictions
     d. Compute final prediction:
        $\hat{y}(i)$ = mean (top-k predictions)
8. Evaluate final predictions using:
   - MAE
   - RMSE
   - MAPE
   - R^2
   - Error Variance
9. Return final prediction $\hat{y}$ and evaluation metrics

E. Model Optimization and Evaluation

The performance of the model is measured in terms of various standard metrics such as MAE, MAPE, RMSE, coefficient of determination, and Error Variance for Stability Analysis. These metrics give a comprehensive idea of the accuracy of the prediction and the error in the prediction. In addition to the average values, the residual values are analyzed to assess the robustness of the prediction, especially during peak demand. Let the actual value be represented by y_i and the predicted value be represented by y, and v denotes the mean of the observed values. With the total data samples N, e_i is the prediction error for the i^{th} observation, computed as $e_i = y_i - y$, and e denotes the mean prediction error.

1. Mean Absolute Error (MAE)
MAE measures the average magnitude of prediction errors without considering their direction.

$$MAE = \frac{1}{N}\sum_{i=1}^{N} |y_i - y| \quad (1)$$

2. Root Mean Square Error (RMSE)
RMSE gives higher importance to larger errors, making it sensitive to peak deviations.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N} (y_i - y)^2} \quad (2)$$

3. Mean Absolute Percentage Error (MAPE)
MAPE expresses error as a percentage, making it scale-independent.

$$MAPE = \frac{100}{N}\sum_{i=1}^{N} \left|\frac{y_i}{y_i} - \frac{y}{y_i}\right|| \quad (3)$$

4. Coefficient of Determination (R^2)
R^2 measures how well the model explains variance in the observed data.

$$R^2 = 1 - \frac{\sum_{i=1}^{N} (y_i - y)^2}{\sum_{i=1}^{N} (y_i - v)^2} \quad (4)$$

5. Error Variance (for Stability Analysis)

$$\sigma^2 = \frac{1}{N}\sum_{i=1}^{N} (e_i - e)^2 \quad (5)$$

III. RESULTS and DISCUSSIONS

This section includes an overall assessment of various machine learning models used in prediction-based applications in grid-oriented systems. Various models, such as linear models, regularized models, tree-based models, kernel-based models, and ensemble-based models, are discussed. In addition, an Adaptive Switching framework is proposed to dynamically choose the best-suited models.

The quantitative assessment of various models, as shown in Table 1, indicates significant differences in performance among various models. In addition, it is evident that the proposed Adaptive Switching framework has the lowest error rates. In other words, the proposed framework has an RMSE of 29.6345 and an MAE of 21.5955. In contrast, other models, such as LightGBM used in this analysis as a baseline model, have an RMSE of 32.2798. This indicates significant improvement in prediction accuracy with the proposed Adaptive Switching framework. In addition, it is evident that the proposed framework reduces error variance to 864.1017. Linear models, such as Linear Regression, Ridge, and Lasso, have relatively higher error rates. This indicates

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limitations of these models in handling non-linear data. In addition, Support Vector Regression models have relatively higher error rates, which indicates low robustness.

The proposed framework workflow and its corresponding results are shown in Table 1, whereas Figs. 1-4 provide an in-depth visual interpretation of model performance and behavior. Table 1 represents the comparative evaluation of all models with respect to various error measures, which shows the effectiveness of the proposed framework. Figures 1 to 4 show an improvement in performance, accuracy of predictions, stability of variance, and dynamic selection of models by the Adaptive Switching framework.

TABLE 1.

PERFORMANCE EVALUATION OF MACHINE LEARNING MODELS.

Model	MAE ↓	RMSE ↓	MAPE (%) ↓	R² ↑	Error Var ↓	RMSE Imp. (%)	Var Red. (%)	Behavior
Adaptive Switching	21.5955	29.6345	0.9785	0.0162	864.1017	8.1949 ↑	14.7136 ↑	Dynamic selection
LightGBM	23.4504	32.2798	0.9745	0.0174	1013.1768	0.0000	0.0000	Best Single
Ridge Regression	23.5119	32.4517	0.9743	0.0177	1052.7609	0.5325 ↓	3.9069 ↓	Static
Linear Regression	23.514	32.4627	0.9742	0.0177	1053.4929	0.5664 ↓	3.9792 ↓	Static
Lasso Regression	24.5905	34.0864	0.9716	0.0186	1160.6233	5.5967 ↓	14.5529 ↓	Static
Random Forest	24.8147	34.4678	0.971	0.0184	1177.1677	6.7781 ↓	16.1858 ↓	Static
CatBoost	26.4132	34.9491	0.9701	0.0194	1150.5123	8.2691 ↓	13.5549 ↓	Static
Support Vector Regression	73.289	98.8466	0.7611	0.0532	9086.206	206.2177 ↓	796.8036 ↓	Static

The visual representation of the visual analysis is presented in the form of Figs. 1 to 4, each of which represents an important aspect of its performance and behavior. These figures provide a comprehensive understanding of the forecasting model by illustrating the relationship between the predicted and actual load values under different scenarios. They also facilitate the evaluation of prediction accuracy, trend consistency, and the model's ability to capture temporal variations in electricity demand. Furthermore, the visualizations help identify deviations, error patterns, and overall forecasting reliability, thereby complementing the quantitative performance metrics presented in the subsequent analysis.

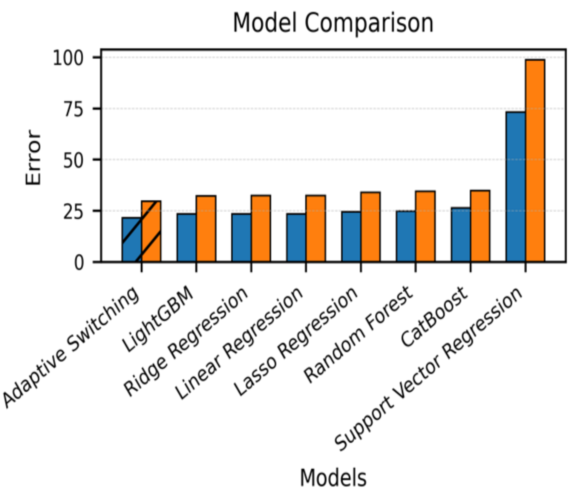

Fig. 1. Comparison of all models showing that the Adaptive Switching model achieves lower errors.

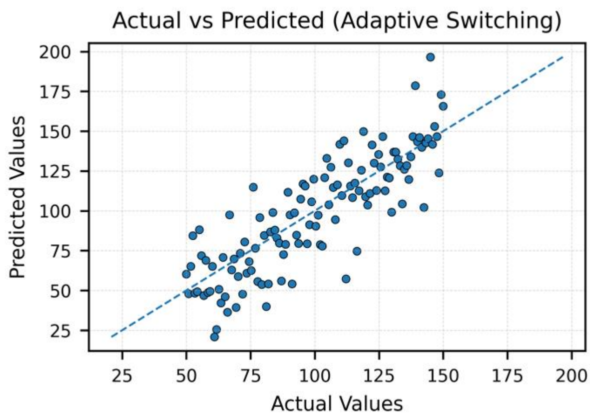

Fig. 2. Actual vs predicted values showing close alignment of the proposed model with real data.

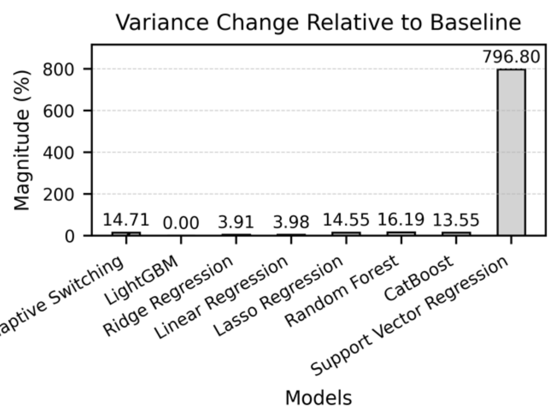

Fig. 3. Variance comparison indicating improved stability of the Adaptive Switching model.

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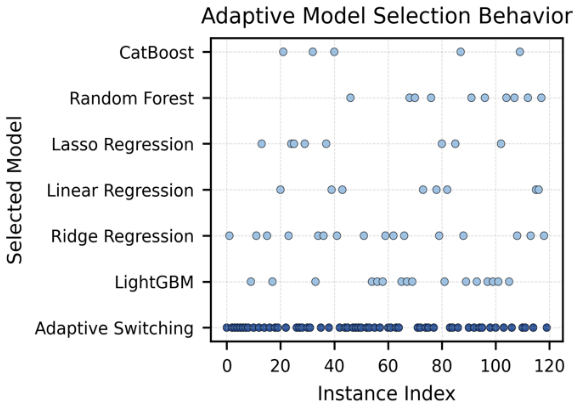

Fig. 4. Model selection behavior showing dynamic switching between models based on input.

IV. CONCLUSION

This research presents an Adaptive Switching framework for predictive modelling in grid-based applications. This is in response to the limitations of conventional predictive modelling techniques. Unlike conventional predictive modelling techniques, which are based on single models, this proposed method can adapt to changing data patterns. This is due to its ability to select the best possible model for every data instance. From the experimental analysis, it is evident that this proposed method is superior to other individual models. This is evident from its superior accuracy and stability. In addition, the reduction in RMSE and error variance is an indication of its ability to provide reliable predictions under diverse conditions. Therefore, it is evident that the proposed framework is efficient in providing precise predictions. In addition, its ability to adapt to changing conditions is an indication of its robustness. This is due to its ability to combine the strengths of individual models.

The importance of this research is its ability to provide precise predictions in modern smart grid-based applications. This is due to its ability to adapt to changing conditions. In modern smart grid-based applications, conditions are highly unpredictable. Therefore, its ability to adapt to changing conditions is an indication of its importance in modern smart grid-based applications. In addition, although this proposed method is efficient in providing precise predictions, it is only applicable to single-region data sets. Therefore, in future, it is recommended to extend this framework to multi-region data sets. In addition, it is recommended to include deep learning-based models in this framework. In addition, it is recommended to include probabilistic models in this framework. In conclusion, this proposed Adaptive Switching framework is efficient in providing precise predictions in complex grid-based applications. Therefore, it is evident that this proposed framework is a significant improvement over conventional predictive modelling techniques in terms of forecasting accuracy.

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