International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14, Issue 06, ACSCON - 2026

Enhancing Iraq's Power Planning Through Singular Spectrum Analysis

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Abstract—Proper electricity demand forecasting is important for grid stability, efficient allocation of energy and reduction of operation expenses. Non-linear and non-stationary power consumption data are often noisy, thus difficult to predict over long horizons. This paper seeks to present a Hybrid Spectral-State Fusion Framework, which involves Adaptive Singular Spectrum Analysis, Dynamic Covariance Kalman Smoothing, and Bidirectional Long Short-Term Memory capabilities to support a high level of accuracy in forecasting. The adaptive decomposition module optimizes dynamically both the window length and component grouping whereas, the Kalman smoother is used to update covariance parameters through the use of residual-driven learning. The preprocessing improvements drastically increase the signal quality before deep temporal model processing. The Bidirectional LSTM learns forward and backward dependencies with the aim of making correct multi-step predictions. It proves itself to be more accurate in its predictions and less prone to error propagation and exponentially stabilized compared to baseline and hybrid models so the approach is applicable to real-time energy management setups.

Keywords—Electricity Demand Forecasting; Adaptive Singular Spectrum Analysis; Kalman Smoothing; Bidirectional LSTM; Time Series Prediction; Hybrid Models; Smart Grid.

I. INTRODUCTION

Modern power system operations and eventually economic dispatch and load balancing depend on electricity demand forecasting, which allows efficient generation planning. As smart grids, integration of renewable energy, and dynamic consumption behavior continue to rapidly expand, it has progressively complicated the process of accurately forecasting them. Many issues affect demand patterns including changes in weather, human activities, economic and seasonal dynamics. These factors create nonlinearities, randomly distributed fluctuations and sudden spikes in load profiles, which negatively influence the use of traditional forecasting techniques. Traditional statistical models can often fail to represent these intricate time dependencies, especially in tasks of multi-step prediction when uncertainty compounds with time [1].

The last few years have seen machine learning and deep learning models getting a lot of attention due to their capacity to predict complex patterns in time series data. Recurrent neural networks and particularly the Long Short-Term Memory models have shown a strong ability to capture long-term dependencies and nonlinear relationships. Bidirectional extensions also improve contextual learning because it works outwards and backwards on data. Alongside these benefits, deep learning models are very susceptible to noise and anomalies in raw electricity demand signals which may compromise predictive accuracy and result in erratic outputs [2].

In order to solve these problems signal preprocessing methods like decomposition and filtering are greatly incorporated. A powerful spectral decomposition technique used to decompose time series data into interpretable components including trend, periodicity and noise, is Singular Spectrum Analysis. Likewise, Kalman filtering and smoothing algorithms have both probability state estimation and smoothing functions. Though, such techniques tend to be based on predetermined parameters and they are not flexible to the dynamic shifts in demand patterns. This makes them less effective in a volatile environment where there is frequent change in the characteristics of loads [3].

Models based on a hybrid of decomposition methods and deep learning frameworks have demonstrated encouraging achievements in the enhancement of the forecasting accuracy. These methods increase the ability of neural networks to learn by eliminating noise and isolating components that are meaningful. However, the current hybrid frameworks are mostly unidirectional in the sense that they only consider preprocessing steps and lack adaptive feedback mechanisms. This limits optimal signal reconstruction and a narrow spectrum of responsiveness to a changing system dynamics [4].

Driven by these shortcomings, this paper presents an adaptive hybrid framework that combines spectral decomposition, probabilistic smoothing, and deep temporal models within a single pipeline. It is a proposed method that allows the description of dynamic parameter tuning with the use of residual feedback, and it enhances the quality of the signal and the strength of forecasting. The framework that includes augmenting the preprocessing flexibility and concurrently integrating it with two-way sequence learning will arrive at consistent yet precise multi-step electricity

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demand predictability befitting the real-world energy administration frameworks [5].

II. LITERATURE SURVEY

This situation has made electricity demand forecasting an important issue in modern power systems because of growing complexity of energy usage patterns and introduction of renewable energy sources. Proper prediction helps to run the grid efficiently, allocate resources optimally, and increase the reliability of energy systems. As penetration of smart grids and distributed energy resources continues, less advanced information-driven and hybrid methods are slowly taking over the established forecasting methods. Such approaches are meant to solve some of the problems, which include nonlinearity, seasonality and uncertainty on load demand. Recent research has highlighted the role of looking at the fusion of statistical, machine learning and optimization methods to help increase the accuracy of the forecast and stability of the system.

The recent innovations in forecasting techniques demonstrate the transition to smart and dynamic models. Methods that concentrate on transmission based forecasting and stability limited operations have shown better performance in renewable based systems [6]. Moreover, the forecasting models have been integrated into energy planning large-scale energy plans to aid low-carbon and efficient energy development policy measures [7]. The sociotechnical perspectives have also been investigated to comprehend the energy transitions towards sustainability and what they imply to predicting practices [8]. Moreover, renewable energy and storage optimization strategies have helped to achieve more accurate predictions in hierarchical control systems [9]. Deep learning applications in building energy predictive modeling has demonstrated an improved accuracy of prediction, as it incorporates intricate temporal correlations [10].

Machine learning-based solutions in smart grids have gone beyond forecasting to include anomalies detection or system monitoring. As an example, to detect electricity theft, sophisticated learning frameworks have been utilized to enhance the security of the grid and to enhance grid performance [11]. Implementation of Internet of Things (IoT) technologies has also made smart buildings technique to acquire data in real-time and manage energy sustainably [12]. Literature on the long-term energy efficiency and emission reduction plans has highlighted the importance of forecasting in policy making and sustainability of the environment [13]. Besides, their application as a component-based method of estimation has been successfully applied to the short-term forecasts of demand providing better performance in dynamic conditions [14]. These advances underscore the increased significance of the intelligent systems in tackling contemporary energy issues.

Forecasting models which are based on artificial intelligence, specifically, neural networks, have become widely considered because they can model nonlinear relationships. Monthly artificial neural network models have been employed with great success to predict monthly electricity demand [15]. The models can work with seasonal fluctuations and complicated consumption behaviors and are thus applicable in the real-world. Moreover, machine learning-based methods of building energy consumption have received much attention, and it has been proven that different algorithms are applicable in predicting user behavior and environmental characteristics [16]. In-depth evaluations have also revealed how forecasting methods developed, focusing on the shift to non-traditional statistical methods and hybrid and AI forecasting models [17].

Proper forecasting models are also important in investment planning and policy analysis in power grid infrastructure. Factor identification methods like fishbone diagram-based methods have been employed to determine the important aspects in making investment decisions [18]. This has been done through forecasting competitions and benchmarking studies, which have given useful information of different models and stimulated the establishment of more powerful techniques [19]. Moreover, it has been acknowledged that hybrid predictive models, which are a combination of more than one algorithm, are more successful in load forecasting applications [20]. They combine strengths of their individual techniques to enhance the accuracy in prediction and flexibility and, as such, these models are most appropriate in complex and uncertain energy environments.

III. METHODOLOGY

The proposed research presents a Hybrid Spectral-State Fusion Framework that aims at enhancing electricity forecasting of demand with adaptive preprocessing and deep temporal modeling. The network combines spectral analysis, linear and probabilistic state estimation as well as bidirectional learning in a sequential, even interactive pipeline. Each of the stages refines the signal in a stepwise way, without altering its computational efficiency. Feedback within the system is critical in dynamically adjusting the parameters in the modules to guarantee that the system is able to respond to changing demand patterns. This methodology has six key steps, the first step being the preprocessing of the data and the final step being the multi-step forecasting. The general system is shown in Figure 1 that depicts the interface between decomposition and smoothing modules and forecasting.

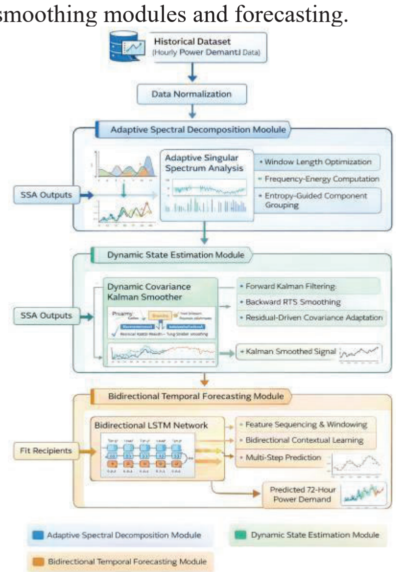

Figure. 1. Diagram of Hybrid Spectral-State Fusion

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A. PREPROCESSING.

The initial step is to gather electricity demand time series data that is credible (smart meters or grid monitoring system). Raw data will have inconsistencies, such as the missing of values, outliers and abnormal times between sampling points. Preprocessing is, therefore, necessary to facilitate the data quality and model preparedness. Interpolation is used to deal with missing values, and statistical tests are used to identify and rectify outliers. This dataset is then scaled to normal range so as to enhance the convergence and stability of models. Time related attributes like hour, day, and seasonal indicators are not lost since they are important in saving the time structure. A rolling window method (as part of the forecasting horizon) is then used to partition the clean data into a training and testing set. This preprocessing phase makes sure that the input signal is consistent, its noise-reduced in a fundamental stage and can be used in other stages to devise more advanced spectral distributions and sequential modelling.

B. ADAPTIVE SINGULAR SPECTRUM ANALYSIS.

This step carries out spectral decomposition of the time series on Adaptive Singular Spectrum Analysis to disaggregate the time series into relevant parts. In contrast to traditional SSA, the method proposed uses dynamic decision making of optimum window length in relation to frequency-energy distribution and periodicity detection. Singular Value Decomposition is used to construct and decompose the trajectory matrix, giving the principal components that show the trends, oscillations and noise. The entropy based grouping mechanism is used to classify the components based on the amount of information and the contribution of the components to the total signal energy. Components that are noise-dominant are detected and removed in the reconstruction. Also, the later, residual, feedback is used to further refine grouping, thresholds, and window parameters. This adaptability method improves the purity of the signal and maintains the vital structural designs. The result is a reconstructed time series with a lower noise and high interpretability, which is a solid baseline to further state estimation and smoothing activities.

C. SIGNAL RECOVERY AND REMAINING FEEDBACK.

After the decomposition, a chosen set of components are reassembled to recreate a pure form of the original signal. This reconstruction is oriented towards retaining trend and seasonal components whilst removing noise-dominant signals. Evaluation of the reconstructed series is through residual analysis where the difference between the original and reconstructed signal is analyzed. Quality in reconstruction is measured using residual statistics including variance, and patterns of distributions. These residues are fed into the Adaptive SSA module again to narrow down component selection and grouping strategies. This feedback loop guarantees successive enhancement in signal quality. The methodology provides interaction between decomposition and evaluation phases, thus overcoming constraints of the static preprocessing methods. The reconstructed signal is both temporally coherent and as much as possible is distortion minimized, which guarantees the retention of critical features necessary to make correct forecasts. This step serves as an intermediate to spectral decomposition and probabilistic smoothing.

D. DYNAMIC COVARIANCE KALMAN FILTERING AND SMOOTHING.

Here, probabilistic state estimation, done by Dynamic Covariance Kalman Filtering and then RauchTungStriebel smoothing is done on the reconstructed signal. The signal is then processed by the Kalman filter, which makes forward pass estimate of the hidden states taking into consideration noise. In contrast to the traditional implementations, the suggested approach dynamically re-estimates process and observation covariance matrices, which are estimated using a residual-driven estimate on variance. This enables the model to fit fluctuating volatility on patterns of demand. Refining once the filtering is finished, the backward smoothing will improve state estimates using future observations, making the signal more stable and predictable. The forward filtering and backward smoothing combination greatly decrease noise, yet maintains structural dependences. This dynamic nature will provide robustness when working in extremely volatile environments, and it will enhance signal continuity. The result is a smooth time series that contains underlying dynamics with minimum uncertainty, which is very appropriate in deep learning based forecasting.

E. BIDIRECTIONAL LONG SHORT-TERM MEMORY (BILSTM) FORECASTING MODEL

The polished signal is subsequently inputted in a Bidirectional Long Short-Term Memory network to have a multi-step forecast. This model works on the time series in two directions, forward and backward, to understand all the temporal dependencies. The architecture has several hidden layers with memory cells which remember the information over a long term period and so, can model nonlinear relationships effectively. To eliminate overfitting, dropout regularization is used, and the converged rate is optimized with adaptive learning rates. The sequences of inputs are obtained via a sliding window scheme that coincides with the forecasting horizon. The model is used to make predictions in the next 72 hours, facilitating the short term operations decision making. Mean Absolute Error and Root Mean Squared Error are some performance metrics to monitor during training. The bidirectional structure provides increased awareness of the context which makes the model to make more accurate and stable forecasts than a unidirectional approach.

F. MODEL EVALUATION AND PERFORMANCE METRICS

The last phase analyses the forecasting effectiveness of the proposed structure with the aid of standard measurements and comparison. The main evaluation measures are the Mean Absolute Error, the Root Mean Squared Error and the Mean Absolute Percentage Error. These measures give an insight into the accuracy of predictions, where the error is distributed, and also the reliability of the model. The proposed model is contrasted

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14, Issue 06, ACSCON - 2026

with such baseline methods like standalone Bidirectional LSTM and standard SSA-Kalman-LSTM hybrids compared on the same conditions of the experiment. Cross-validation methods provide the strength and generalization among various segments of data. The prediction trends, error patterns, and convergence behavior are analyzed by the use of visualization tools. The computational efficiency and scaling to be used in real-time deployment are also evaluated. Findings indicate that the adaptive hybrid structure has a high level of accuracy, less errors spreading and is more stable in long horizon predictions, which does justify it as a useful component on the current smart grid projection.

IV. Result and Discussion

Hybrid Spectral-State Fusion Framework was tested and assessed considering the real-world electricity demand time series on the same training and testing conditions in order to compare fairly with planned models. A rolling window technique was used to segment the dataset, and a fixed forecasting horizon of 72 hours was used. Mean Absolute Error, Root Mean Squared Error, and Mean Absolute Percentage error were used as performance measures. The findings indicate the importance of preprocessing in enhancing the accuracy of forecasts. The Bidirectional LSTM model standing alone performed decently but was unstable when there were changes in peak demand. This instability was mainly caused by presence of noise and irregular spikes in the raw data which influenced the ability of the model to learn.

Combination of Singular Spectrum Analysis and Kalman Smoothing enhanced the quality of the signals and the performance of better forecasts was achieved. The traditional hybrid model, however, was dependent on non-adaptive parameters and this reduced its flexibility to changing loads. Consequently, the dynamic even though noise was reduced, the model could not be consistent when the intervals were very volatile. Contrary to this, the suggested adaptive framework dynamically updated decomposition and smoothing parameters, which relies on residual feedback, thus providing better signal reconstruction and stability. This caused a more predictable trend in prediction, particularly when there was consistently a sudden spike in demand and in transitions.

Table 1 compares the performance of forecasting performance between various models. It is clear that the proposed model had the lowest values of the errors compared to all the methods. The decreased Mean Absolute Error and the root mean squared error shows that the accuracy of prediction is at a higher value and the lower percentage error produced by the mean absolute reflects a greater generalization at the different levels of the demand.

TABLE I. COMPARISON OF THE PERFORMANCE OF FORECASTING MODELS.

Model	MAE	RMSE	MAPE (%)
Bidirectional LSTM	5.82	7.45	6.91
SSA–Kalman–BiLSTM	4.36	5.98	5.12
Proposed Adaptive Hybrid Model	3.21	4.67	3.84

This is evident in the results that indicate that the proposed method significantly performs better than the standalone model, as well as the conventional hybrid model. It is improved primarily due to adaptive spectral decomposition and dynamic covariance estimation, which is used to facilitate signal purity prior to forecasting given by deep learning. Moreover, the decreasing error propagation with the successive predictions proves the high robustness of the framework to long-horizon forecasting scenarios.

Table 2 will further be used to discuss performance at different demand conditions by giving error metrics at the different loads including low, medium and peak demand conditions. The proposed model remains the same at all intervals whereas the errors are higher in the case of the baseline models.

TABLE II. ANALYSIS OF ERROR AT DIFFERENT LEVELS OF DEMAND.

Demand Level	Model	MAE	RMSE
Low Demand	BiLSTM	3.45	4.12
Low Demand	Proposed Model	2.18	3.01
Medium Demand	BiLSTM	5.76	6.89
Medium Demand	Proposed Model	3.42	4.55
Peak Demand	BiLSTM	8.92	10.15
Peak Demand	Proposed Model	4.87	6.12

As indicated in the table, the proposed framework works well in peak demand situations with error margins being very small as compared to the standalone model. This betterment is of particular significance to real-life and practical application, where precise prediction in the high-demand times is key to the grid integrity, and thermal scheduling.

Besides quantitative analysis, visual comparisons were conducted to evaluate the trends in predictions. In Figure 2, the actual and the predicted demand value in the proposed model is compared. The forecast curve is very similar to the observed demand pattern as both smooth trends and sharp peaks with sudden high demand are well pinpointed.

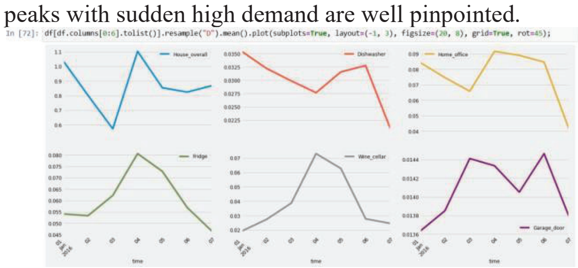

Figure. 2. Actual vs Predicted Electricity Demand (Proposed Model*)*

The excellent meshing of the true and model values indicates that the hybrid approach suggested is effective in both faithfulness to time-dependent relationships and resilient to volatility. Small deviations are noticed in extreme spikes, and the consistency of the trend is good.

The convergence behavior of errors in training is indicated in figure 3. The suggested model has a stronger learning efficiency and stability, as it converges faster and ends up with a smaller final loss in comparison to the baseline models.

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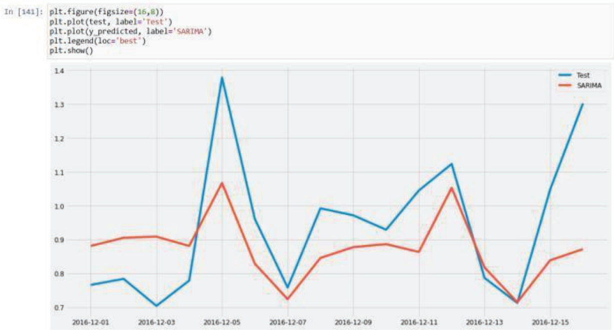

Figure. 3. The training loss convergence comparison

has a strong effect of improving the training of the model because it provides cleaner input signals. This simplifies what the neural network is learning and helps the neural network to concentrate on meaningful patterns instead of noise.

On the whole, the findings prove that the suggested Hybrid Spectral-State Fusion Framework brings significant enhancements in accuracy, stability and robustness of forecasting. Adaptive decomposition, dynamic smoothing, and bidirectional learning are integrated together to produce a synergistic effect to overcome the constraints of current methods. Not only does the framework minimize errors in prediction but also guarantees uniformity of performance in cases of different demand conditions thus very appropriate in practical applications of smart grid in real-time.

V. CONCLUSION

This paper introduced a ground breaking Hybrid Spectral-State Fusion Framework of stable and accurate electricity demand prediction. The suggested solution employs dynamic covariance-based state estimation, adaptive spectral decomposition and bidirectional deep learning to overcome the issues of nonlinearity, noise and volatility of power consumption data. The framework improves signal quality before temporal modelling, introducing Adaptive Singular Spectrum Analysis and Dynamic Covariance Kalman Smoothing, to allow the Bidirectional LSTM network to capture more meaningful patterns. The findings show that the suggested approach can considerably enhance accuracy in predictions, minimise the error spread, and be consistent between different demand situations. It is also lightweight in its computational design which renders it appropriate to be deployed in actual energy control systems in real-time.

Regarding future employment, the framework can be expanded to cover exogenous factors like weather conditions and economy-related factors to increase prediction accuracy further. Also, further improvements can be made on long-range dependency modeling through the incorporation of attention mechanisms or transformer-based architectures. A deeper investigation of online learning methods of real-time adaptability and scalability of testing in various geographical areas will further reinforce the relevance of the proposed system.

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