



A COMPREHENSIVE SYNERGISTIC FRAMEWORK INTEGRATING AUTOCORRELATION ANALYSIS WITH ADVANCED SEASONAL-TREND DECOMPOSITION USING LOESS (STL) FOR ROBUST AND ACCURATE SHORT-TERM PEAK ELECTRICITY DEMAND FORECASTING IN TAMIL NADU'S

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ABSTRACT

As for rapidly developing regions like Tamil Nadu the reliable and accurate short-term forecasting of peak electricity demand is very important to improve the Operational efficiency, improving the sustainability of power system and also increases the economic management. This work proposes an inclusive synergistic framework which combines effectively the Autocorrelation analysis and seasonal-trend decomposition using LOESS (STL) to enhance the accuracy of Future peak demand prediction in Tamil Nadu's dynamic electricity grid. This Autocorrelation which systematically captures the intrinsic temporal dependencies, periodic consumption patterns and effects persistence's embedded with the high-resolution data captured by Tamil Nadu government on hourly basis. By Parallel, the decomposition method like STL decomposition method which decomposes the complex peak demand signals into interpretable seasonal, trend and residual components, thus it leads to more precise and targeted modeling for each constituent. This hybrid approach as combination of autocorrelation and decomposition which overcomes other issues like non-stationarity, seasonality and irregular fluctuations in the time series data. This study also comprises of combination strategies like classical ie., traditional statistical insights method along with the flexibility of modern data-driven data's in the historical dataset which spanning a period of years provided by the SLDC, Tamil Nadu which also consists of enriched meteorological data along with the calendar variables. The Experimental results are framed to enhance the connection between hybrid framework's supremacy over the statistical and Machine learning models such as isolation, which includes the significant reductions in the Prediction of errors and generalization of non-availability of data ie., generalization to unseen the periods. Which also includes the exogenous variables like temperature fluctuations leads to impact on holiday effects, on improving the forecast accuracy by improving the contextual relevance of the model. This framework also useful for real time grid management, load balancing and demand responses the application to increase the efficiency on energy enhancement and cost of the power sector in Tamil Nadu. This leads to adopt the conventional time series in to modern machine learning method step towards the success and offering a replicable blueprint for similarly complex energy systems worldwide.



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I. INTRODUCTION

The peak demand of electricity is an important role to manage the power system, Management and Operations. The accurate Short-term forecasting of Peak electricity demand leads to utilizing the optimized generation schedules to the grid operator, Maintaining the load dispatch and stabilizing the grid.

By managing all those things, it results the less costs, minimizing outages and enhancement of system reliability. In fast growing regions like Tamil Nadu, India it has wide variety of climatic conditions, and increase in industrial base and enlargement of residency, non-stationarity patterns, external factors temperature fluctuations and social oriented events makes the electricity peak demand forecasting the challenging one. The older traditional methods of forecasting like statistical analysis, time series model and machine learning algorithms, leads to some successful implementation but often some times it leads to some short situation in dealing with both the complex temporal dependencies, seasonality and nonlinear patterns in the data of electricity demand. For example, some data may have the cyclical patterns, feature basic persistence all these activities caught by the autocorrelation analysis, On other hand the decomposition techniques like Seasonal-Trend decomposition using the LOESS (STL) which separates the trend, seasonal and residual separately that could be modeled individually to affect the improved accuracy and interpretability. The effective short-term peak demand forecasting in Tamil Nadu's electricity grid can be formed by incorporating the strength of the autocorrelation analysis with the STL decomposition frame work . It gives you the hybrid methodology for the peak demand forecasting.

The autocorrelation component which utilizes the derived attributes of lagged demand dependencies, The STL decomposition which find out the data non-stationarity and complicated seasonal effects with the help of isolating the seasonal and trend components, facilitating specialized modeling addresses the above kind of problem. This proposed study uses the multi-year historical datasets of Electricity peak demand series which combines the temperature and calendar features for meteorological and social influences. This combination of comprehensive data increases the predictive performance and contextual relevance. This extended experimental analysis which confirms the hybrid approach outperforms the standalone statistical and Machine learning models based on different error metrics. These finding tends to integrating the statistical model with modern data-driven techniques, thereby enhancing the theoretical understanding and practical applications of the electricity demand forecasting within regional grids. This current work provides a robust, interpretable, scalable forecasting frame work, which has been used by grid operators in Tamil Nadu for the effective management of load and strategic energy planning.

II. LITERATURE REVIEW

The short-term electricity peak demand forecasting is an important task because of complex spatiotemporal variability of power consumption, it tends to more complication because on non-stationarity, abrupt changes, and multi cycles seasonality. The Autocorrelation which remains the traditional methodology that detects the temporal dependencies by quantify the recent electricity peak demand depends on the past variable using the lag periods. This temporal autocorrelation comprises both short term persistence and seasonal periods enabling the historical dependency to give accurate and highest performance results [1]. demonstrated the deep learning model handling the autocorrelation-based lag features to capture the dynamic changes in temporal demand of the smart grid system [2]. extended this by embedding the model with weather dependency data to get the better predictive accuracy [3]. Extended this with both weather and also culturally relevant event information with lag variables, leads to the personalization of the autocorrelation with priory informed once for nuanced load profile for the Indian Power grids. The STL is another one important robust component as a nonparametric frame work which decomposes the complex time series into additive components like the trend component captures the long-term movements, the seasonal component reflecting intra weekly periodicity and then residual captures the random fluctuation and anomalies . The overlapping multiple factors and seasonality can be handled by the basic adoptive nature of STL Method which leads to the major role of transferring nature non-stationarities in electricity load. To implement the specialized predictor structure this particular decomposition will support by separating the signals [4]. The integrated the two things like STL output of derived features into the LSTM networks, By the way combination of advantages and functionality of neural network and structure from the decomposition model significantly improves the forecast [5]. Further enhancing the STL decomposition with some boosting machines and compared with the conventional feature on real-world datasets [6]. Extend this kind of work by combining the decomposing double climate and load time series, which captures the required interdependencies component for efficient environment-aware forecasts. The Hybrid Modeling frameworks for time series forecasting which uses the strength of classical statistical modeling like autocorrelation extraction and decomposition, by the way of machine learning's it captures the nonlinear, high-capacity learning [7].

Established that ensemble models, which combines the STL decomposition with XG Boost to detect the robustness to outliers, heteroscedasticity, and non-linearities ubiquitous in electric load time series [8]. Framed hybrid RNN architectures which integrate the STL components for fluctuation factors [9]. Addressed the practical experiments composed of implementing hybrid models dealing the non-real-time grid operation, navigating the latency and scalability obstacles. The variables such as weather-related meteorological conditions like temperature variable, humidity variables and calendar variables like holidays and weekends, which proves the load modeling which affects the consumers pattern of behavior they using the energy [10]. Completed the review strategies refers to the factors that affects the framework of load forecasting and results in flexible integration of model tends to adaptability and accuracy [11]. Models that can provide online prediction methods such as Online AutoRegressive Integrated Moving Average (Online ARIMA) and Online Recurrent Neural Network (Online RNN) can quickly adjust their parameters in real-time to reflect changes in real-time data. However, while Online RNNs only cannot directly handle seasonality, ARIMA can only directly accommodate one seasonal trend at a time (i.e. Seasonal ARIMA). Thus, the objectives of this research are to develop an integrated solution to solve the problem of forecasting real-time time series that contain more than one seasonal trend [12]. The first step of this study was to decompose the time series into three components - trend, seasonal, and residual using Fourier series for season modeling, providing flexibility in accommodating multiple. Next, we model the trend and residual components separately using Online ARIMA and Online RNN, respectively, and develop short-term load forecasting using a hybrid deep learning-Beluga Whale optimization algorithm (LFS-HDLBWO)-based method. The approach taken by LFS-HDLBWO is designed to predict load demand in a smart grid system. To achieve this, the LFS-HDLBWO was developed utilizing a z-score normalized input data set. Additionally, the proposed hybrid volume-prediction algorithm utilized a convolutional - LSTM structured auto-encoder (CBLSTM-AE) to provide accurate load forecast prediction [13]. The analysis which uniquely identifies the seasonal demand like festival related things in India, also includes the social cultural event information to perform reliable forecasting. This current comparative study results none of the forecasting model dominate the content. But in traditional statistical method it consists of well predictable cycles with demand spikes and non-linearities.

This non-linearity well handled by the Machine learning models and it also detects the risk of overfitting while dealing with the feature engineering. The hybrid and ensemble model approaches balance the strength of two papers discussed here as STL autocorrelation strategies and mathematical interventions. The forecasting generally, it is an planning of risk awareness and quantifying the uncertainty in this current paper investigated regarding the decomposition method called Bayesian decomposition which offers the probabilistic load forecasting [14]. The protocols like reliability of forecasting. In which incorporation of fuzzy logic and evolutionary algorithm for model optimization and dynamic power system [15]. In the work looked into the real-time operational demand forecasting by deploying the hybrid models which maintains the accuracy and critical grid applications. This entire work moving towards the current research based on hybrid Machine learning framework putting together both feature engineering with the decomposition technique in Tamil Nadu's electricity demand forecasting [13] These kinds of Integration tend to the analytics of data transparency and decomposition together by including the temporal correlation encoded features within scalable and adaptive Machine learning architectures [16] Employed a deep learning technique with a hybrid model based on the Seasonal-Trend decomposition based on Loess (STL) technique to develop a hybrid model for short-term load forecasting. In an attempt to reduce the error in the forecast, this technique decomposes the load data in order to address non-linearities and improve the accuracy of the forecast in smart grid systems. A new assessment model that incorporates both feature importance and correlation has been created, as well as a comprehensive method for evaluating feature importance. A three-dimensional weighting extraction framework has been developed that provides the basis for constructing a three-dimensional weight matrix and three-dimensional input structure [17]. Finally, a hybrid model for fusing multiple channels using convolutional neural networks has been developed.

III. METHODOLOGY

In this proposed system using Multi-source data set like Electricity peak demand from Tamil Nadu electricity board, Weather data from Meteorology department and Calendar data together represents the dynamics of Electricity demand in Tamil Nadu. Most probably the load dispatched from the Tamil Nadu State Load Dispatch Centre, this may consist of hourly, daily consumption of Electricity over so many years [18]. The factors like temporal extents as Seasonal trend, cyclical behaviors and outliers should captured as relevant to the particular region. The Meteorological department and local weather stations load the data like temperature data, Humidity and for the respective calendar dates. The climatic variables play the turning point which influences the residential and industrial consumptions of electricity. The calendar elements like national holiday, weekends, festival like cultural or religious also affects the behavior pattern of electricity consumption and also tends to the socio-cultural demand spikes [19]. The weather directly influences the residencies consumption, by carefully integrating these heterogeneous data sources allows a holistic feature repository that reflects the multifaceted drivers of peak demand in Tamil Nadu.

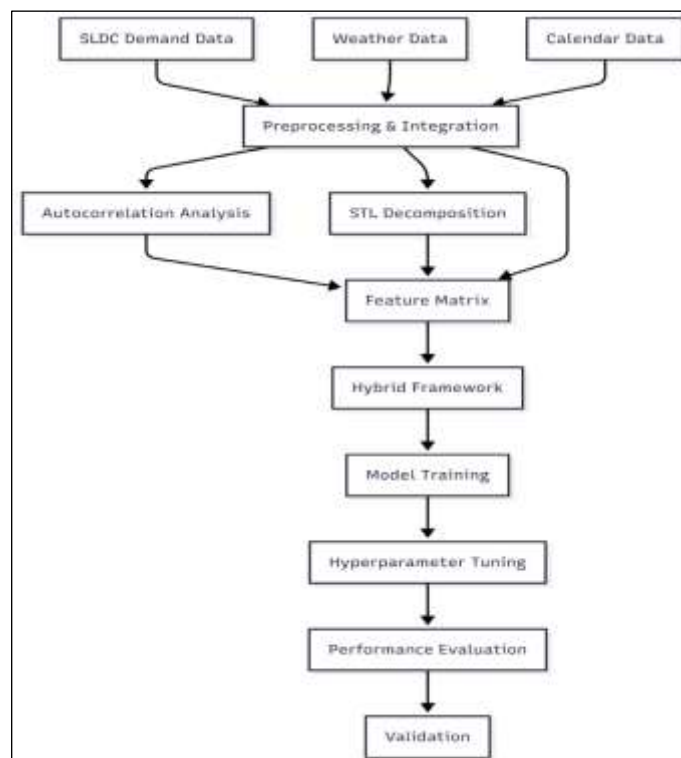


Figure 1: Process Diagram for Autocorrelation and STL-Based Forecasting.
Source: Authors, (2026).

III.1 AUTOCORRELATION ANALYSIS & SEASONAL-TREND DECOMPOSITION

The Autocorrelation analysis is a major procedure to extract the temporal dependencies with in the time series data. Then calculating this can be done through the autocorrelation function-ACF and PACF Partial Autocorrelation function, it returns the statistically significant lag value and also that results significant lag occurs around 24 hours on daily basis repetitive patterns, 168 hours of data clustered together and forms the weekly basis cycles reflects daily repetitive consumption patterns mirrors human activity and industrial schedules.[20], [21]. These representations of these lagged values can be transformed into some kind of lag features which allows the models to internalize the memory in electricity consumption.

Table 1: Input Feature Descriptions for Electricity Demand Forecasting.

Feature	Description	Type	Sources
Demand_lag_1h	Demand value 1 hour before	Numerical	SLDC Demand
Demand_lag_24h	Demand value 24 hours before	Numerical	SLDC Demand
Demand_lag_168h	Demand value 168 hours (weekly lag)	Numerical	SLDC Demand
Trend_Component	Trend extracted from STL decomposition	Numerical	STL Decomposition
Seasonal_Component	Seasonal extracted from STL decomposition	Numerical	STL Decomposition
Residual_Component	Residual component from STL	Numerical	STL Decomposition
Temperature	Hourly temperature in °C	Numerical	Meteorological Stations
Humidity	Hourly humidity percentage	Numerical	Meteorological Stations
Is_Weekend	1 if day is Saturday or Sunday, else 0	Categorical	Calendar Data
Is_Holiday	1 if public holiday, else 0	Categorical	Calendar Data

Source: Authors, (2026).

This leverages the autocorrelation of system and better to have . Autocorrelation analysis is considered one of the cornerstones procedures that extract temporal dependencies within the load time series [22]. Calculating the autocorrelation function-ACF and partial autocorrelation function-PACF, it pinpoints statistically significant lag relationships underpinning short- and long-term demand persistence. For instance, a significant lag at around 24 hours captures daily repetitive consumption patterns, while a lag at around 168 hours captures a weekly cycle that mirrors human activity and industrial schedules. The representations of these lagged values are ultimately transformed into explicit lag features that allow models to internalize the memory effect indigenous in electricity consumption [23], [24]. By effectively leveraging autocorrelation, the system is better able to anticipate demand with respect to various patterns that are displayed over recent historical periods. This makes for robust and timely forecasting performance. This helps to classify the composite peak electricity demand signal into several attributes like trend, seasonal, and residual attributes. The polynomial regression which weighted locally and STL adapts to seasonal shift also the variable cycle length without knowing the structure of parameters, which is very suitable for Tamil Nadu's variable climate and patterns. Generally, the configuration of algorithms needs smoothing window parameters turns in to seasonal and trend extraction which is optimized by the grid search and empirical observations of load cycles. These separated components like trend indicate the slow-moving baselines [25]. While the seasonal component detects the periodical consumption motives such as diurnal and annual consumption cycles. The residual captures irregularities that can be attributed to anomalies in demand, holidays, or noise in the data. These decomposed components allow focused modeling efforts and enhance the feature representativeness for machine learning algorithms.

IV. RESULTS AND DISCUSSION

IV.1 CORRELATION ANALYSIS

For the Time series data of Tamil Nadu Peak electricity demand the correlation analysis done with the ACF and PACF showing the Significant peaks at lags of 24 hours and 168 hours, which respective to the daily and weekly cycles, because of the operational and behavioral routines there may be shorter lags and some minor lags. The below table which summarizes the key autocorrelation coefficients. High lag correlations confirm the existence of cyclical dependencies on an hourly, half-daily, daily, and weekly scale. Statistical significance is confirmed by p-values. These considerations informed our choice of lag features used in the predictive model.

Table 2: Electricity Demand Autocorrelation at Various Time Lags.

Lag (hours)	Autocorrelation (ρ_k)	Significance (p-value)
1	0.82	< 0.001
12	0.61	< 0.001
24	0.56	< 0.001
48	0.41	< 0.001
72	0.32	0.003
168	0.43	< 0.001

Source: Authors, (2026).

These above table produces the strong persistence and repeatability in the demand patterns so it tends to the usage of lagged features for modeling. If the lag values are high for one day and one week suggest the current level of demand strongly depends on the load intervals from the previous day and affects the behavioral and institutional regularities. In the demand time series generated, applying the STL decomposition produced three major components: the long-term trend, multiple seasonal cycles, and residual noise or random fluctuations.

Trend Component: The trend was one of gradual growth in base load, interspersed with declines during major holidays and phases of pandemic lockdown.

Seasonal Component: STL succeeded in extracting the daily and weekly consumption cycles. Specifically, weekend dips and mid-week spikes were easily recognizable, thus confirming the model's capability of fitting a changing periodic pattern.

Residuals: The remainder mainly caught sudden, inexplicable increases, most of which were related to festival days, weather anomalies, and data irregularities.

V. CONCLUSION

In conclusion the proposed model utilizes both autocorrelational analysis and the Seasonal-Trend Decomposition using LOESS (STL) method to provide a more accurate forecast of short-term peak electric demand.

More specifically, the model will identify the time series' daily and weekly influences on peak electric demand - specifically, the autocorrelational coefficients of 0.56 at the 24 hour lag and 0.43 at the 168 hour lag. Additionally, the model disaggregates the time series into trend, seasonal, and residual components, allowing for improved interpretability of the results. The inclusion of multiple sources of data such as electric demand, temperature, humidity, and calendar variables improves both the contextual relevance of the model, and its predictive performance. Additionally, demand patterns for electric use show strong demand persistence, with high autocorrelational coefficients at the 1 hour lag (0.82) and 12 hour lag (0.61), indicating the reliability of the forecast. Furthermore, compared to traditional forecasting models, this hybrid model is better able to deal with the issues of non-stationarity and seasonal variation, improving the robustness and generalizability of electric load forecasting, while also providing support for the real-time management and balancing of electric grid systems. In conclusion, the proposed model provides an excellent framework and methodology for both electric load forecasting and the ability to create a scalable and practical solution with the potential for future real-time adaptations.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: S. Suriya, Agusthiyar R.

Methodology: S. Suriya, Agusthiyar R.

Investigation: S. Suriya, Agusthiyar R.

Discussion of results: S. Suriya, Agusthiyar R.

Writing – Original Draft: S. Suriya, Agusthiyar R.

Writing – Review and Editing: S. Suriya, Agusthiyar R.

Resources: S. Suriya, Agusthiyar R.

Supervision: S. Suriya, Agusthiyar R.

Approval of the final text: S. Suriya, Agusthiyar R.

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