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Improving Monthly Electricity Demand Forecasts through HP-Based Decomposition and Hybrid RNN–ARIMA Learning

Yifan Zhao^{1*}, Liang Chen¹

Abstract

Monthly electricity demand exhibits both persistent upward trends and recurring seasonal patterns, which together pose major obstacles to reliable forecasting. This research, therefore, introduces a single-variable time-series prediction strategy that uses the Hodrick-Prescott (HP) filter to decompose the demand sequence into a smooth trend component and a seasonal component. The trend is modeled using an autoregressive integrated moving-average (ARIMA) model, while recurrent neural networks (RNNs) are employed to capture recurring seasonal behavior. The complete forecast results from combining the two separate predictions. Model effectiveness is tested on Guangzhou's monthly total electricity usage records. When benchmarked against established techniques, including Holt-Winters, Seasonal ARIMA, and error-trend-seasonal (ETS), the developed HP_RNN_ARIMA combined approach lowers mean absolute percentage error (MAPE), root mean square error (RMSE), and mean absolute error (MAE) in the ranges of approximately 9.70% to 35.66%, 14.18% to 35.06%, and 20.01% to 41.92%, respectively. Compared with individual neural network models such as backpropagation (BP), RNNs, and long short-term memory (LSTM), the new model reduces MAPE, RMSE, and MAE by 9.05%-44.02%, 20.88%-51.74%, and 29.53%-56.23%, respectively. Compared with alternative hybrid techniques, the reductions in these error measures range from 3.60% to 33.39%, 4.27% to 36.67%, and 4.43% to 44.87%. The model also attains the best scores on Willmott's index (WI) and Legates and McCabe's index (LMI), demonstrating stronger agreement with observed values. Overall, decomposing the series with the HP filter and modeling the resulting components independently yields a clear improvement in forecast quality.

Keywords Electricity demand forecasting, Hodrick-Prescott filter, Recurrent neural networks, Autoregressive integrated moving average model

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Introduction

Reliable electricity load prediction is fundamental for strategic energy planning, transmission network expansion, and day-to-day utility management, and it plays a central role in ensuring power system security, operational stability, and resource efficiency [1]. As worldwide efforts accelerate toward decarbonized energy systems, large-scale adoption of variable renewables—particularly solar and wind—has created serious difficulties for maintaining grid balance. In parallel, continued economic development and changing weather patterns have noticeably intensified swings in electricity consumption in recent years. These dual pressures—the rising proportion of intermittent renewables and greater demand volatility—make precise demand forecasting increasingly essential.

Forecasting horizons for electricity demand are commonly grouped into three categories: long-term (spanning 5 to 10 years), medium-term (ranging from 1 month to 5 years), and short-term (covering 1 hour to 1 week) [2]. The majority of earlier studies have emphasized short-term load forecasting, leaving medium- and long-term demand prediction comparatively underexplored [3]. Monthly forecasts belong to the medium-term group. Monthly demand series characteristically show steady long-run growth combined with distinct seasonal oscillations; the coexistence of these two dynamics significantly complicates the construction of effective predictive models [4].

To achieve more accurate monthly electricity demand forecasts, this work presents an integrated hybrid framework that combines the Hodrick-Prescott (HP) filter, the autoregressive integrated moving-average (ARIMA) model, and recurrent neural networks (RNNs). Decomposition begins by passing the raw demand data through the HP filter, which extracts a secular trend component and a seasonal/cyclical component. ARIMA is subsequently used to generate trend predictions, while RNNs are tasked with forecasting the seasonal fluctuations. The two forecasted parts are then summed to form the complete monthly prediction. The principal features and strengths of this hybrid approach can be summarized as follows.

First, the HP filter cleanly disentangles the underlying long-term movement from periodic oscillations, enabling tailored modeling for each extracted series and limiting undesirable interactions between components during parameter estimation. Compared with procedures that partition the original data into numerous subseries, this filter produces just two outputs—trend and cyclical—preserving more information and streamlining the modeling process. Second, secular trends are typically shaped by slow-moving drivers such as macroeconomic expansion and population dynamics, which give rise to strong serial dependence; the AR and MA terms in ARIMA are specifically designed to handle this behavior. Third, seasonal movements, driven mainly by weather-related factors, produce large and regular swings. Furthermore, variations in per capita income frequently cause heteroskedasticity in economic series, a property that also characterizes the seasonal component. RNNs are particularly effective here because they can learn long-range temporal dependencies and approximate complex nonlinear patterns. Lastly, empirical testing confirms the superior predictive power of the proposed hybrid. Results from simulations indicate clear outperformance over standard univariate time series methods, standalone neural architectures, and competing hybrid neural network models.

The present research develops a hybrid prediction technique informed by a detailed examination of the structural properties of monthly electricity demand. A major benefit is its very limited need for detailed exogenous socioeconomic or weather variables, which are frequently unavailable or themselves hard to forecast reliably. In contrast to multivariate approaches that require accurate projections of external factors, the proposed method largely sidesteps this difficulty. By decomposing the series and modeling the parts separately, the framework better identifies and exploits the dominant behaviors present in each subsequence, yielding higher accuracy than applying machine learning or classical econometric models directly to the raw data. Beyond improved precision, the model supplies useful guidance for capacity planning, real-time grid operations, and end-user consumption management. Its wide relevance extends to revealing shifts in underlying economic trajectories and providing actionable information to participants in electricity trading and carbon markets. For instance, deseasonalized ARIMA projections help uncover fundamental economic signals, while the RNN-based seasonal forecasts supply complementary insights valuable to market actors in both power and emissions trading.

Literature Review

Forecasting models within a multivariate framework

A substantial portion of earlier research on monthly electricity demand prediction has focused on multivariate modeling. For instance, Chabouni *et al.* [5] employed a causality-driven multiple regression to investigate the linkages among electricity demand, ambient temperature, and other influential factors in Algeria. Liu *et al.* [6] analyzed how temperature fluctuations affect household electricity consumption. Zheng *et al.* [7] developed a predictive model of electricity usage that incorporates a range of socioeconomic and climatic variables. These investigations generally seek to anticipate demand changes by accounting for variations in economic, demographic, and meteorological drivers. Their primary

advantage is the ability to measure and interpret the connections between demand and explanatory factors, yielding results that are both understandable and economically relevant.

Recent progress in artificial intelligence has enabled neural network-based approaches to deliver impressive forecasting results in fields such as natural resources [8, 9], environmental studies [10], and energy systems [11, 12]. In electricity demand forecasting, several studies have integrated neural networks into multivariate models. Huang *et al.* [13] combined particle swarm optimization with support vector regression, relying on climate inputs. Ghimire *et al.* [14] presented a transformer architecture with multi-head self-attention that included localized weather data. Pallonetto *et al.* [15] evaluated the predictive capabilities of long short-term memory (LSTM) networks and support vector machines (SVMs). Obringer *et al.* [16] proposed a multi-sector, multivariate structure to assess climate impacts on joint electricity and natural gas consumption. Liu *et al.* [17] applied artificial neural networks (ANNs), support vector regression (SVR), and gradient boosting decision trees (GBDTs) to evaluate the influence of climate and socioeconomic trends on extended monthly electricity demand in Hong Kong. Ghimire *et al.* [18] introduced an interpretable, deeply integrated neural network for demand prediction. Miraki *et al.* [19] proposed a denoising diffusion-based technique for probabilistic multivariate time-series forecasting.

Although AI-driven models typically outperform traditional multiple regression in predictive power, they provide reduced transparency and interpretability. Furthermore, the effectiveness of multivariate approaches heavily depends on the reliability of forecasts for the included exogenous variables. For example, since gross domestic product (GDP) strongly influences electricity demand, incorporating GDP requires dependable future GDP estimates to maintain model accuracy.

Forecasting models within a univariate framework

Other lines of research have pursued univariate strategies, relying solely on past electricity demand values to generate future projections. Widely adopted techniques in this category include Holt-Winters exponential smoothing [20, 21], autoregressive integrated moving average (ARIMA) models [22, 23], and the Prophet framework [24]. As prediction techniques have advanced, scholars have increasingly acknowledged that no single conventional model adequately captures the complex dynamics of monthly series, prompting greater exploration of hybrid methods. Examples include de Oliveira and Cyrino Oliveira [25], who proposed a bagging ensemble that merges ARIMA with exponential smoothing. Tang *et al.* [26] developed an enhanced seasonal index approach tailored for grey model-based forecasts of power consumption. Bakare *et al.* [27] combined gene expression programming with adaptive neuro-fuzzy inference systems to improve industrial demand predictions. Wang *et al.* [28] integrated ensemble empirical mode decomposition and particle swarm optimization with SVR, achieving substantial reductions in forecast error for medium-term forecasts. Du *et al.* [29] optimized both point and interval predictions simultaneously by coupling time series decomposition with deep learning. Dong *et al.* [30] presented a hybrid SVR model enhanced by a chaotic cuckoo search algorithm.

Univariate models are valued for their strong predictive performance, structural simplicity, and low data demands, which prove particularly advantageous when comprehensive socioeconomic, demographic, or weather datasets are scarce or unavailable. In real-world settings, such auxiliary information is often available only at quarterly or annual intervals, which creates difficulties for monthly-scale forecasting.

Forecasting models based on decomposition-integration structure

One widely adopted strategy in hybrid forecasting entails breaking the original time series into separate components, applying targeted prediction methods to each, and then recombining the outputs to produce the final forecast [31, 32]. Common decomposition tools encompass moving averages, polynomial fitting, spline interpolation, empirical mode decomposition (EMD), seasonal-trend decomposition using LOESS (STL), and the Hodrick-Prescott (HP) filter.

González-Romera *et al.* [33] utilized moving averages to isolate trend and irregular components in electricity demand, applying neural networks to the trend and Fourier analysis to the residuals. Zhu *et al.* [34] combined seasonal ARIMA (SARIMA) with particle swarm optimization after applying first-order moving average smoothing. Gonzalez-Romera *et al.*

[35] extracted characteristics from monthly demand using moving averages together with cubic splines. Jaramillo-Morán *et al.* [36] decomposed the series into trend and fluctuation parts, then subdivided the fluctuations into six frequency bands, each forecasted separately via neural networks.

Xiong *et al.* [37] fused EMD with support vector machines. Wang *et al.* [28] incorporated EMD, sample entropy, particle swarm optimization, and SVR. Shao *et al.* [38] merged semi-parametric techniques with EMD. Gao *et al.* [39] introduced an improved variational mode decomposition (VMD) paired with Sparrow search–optimized extreme learning machines. Zhang *et al.* [40] built a hybrid load prediction model centered on VMD. Niu *et al.* [41] proposed a two-stage decomposition using STL followed by VMD, with SVR parameters tuned by the grey wolf optimizer. Park *et al.* [42] and Li *et al.* [43] relied on STL decomposition in their respective forecasting frameworks. Zhang and Hong [44] employed complete ensemble empirical mode decomposition with adaptive noise for hybrid model construction.

Beyond these approaches, the HP filter has found application in several hybrid schemes. Yuan *et al.* [45] used it to separate electricity consumption series, while Cancelo *et al.* [46] extracted the trend component from Spain's monthly demand data. Bunnoon *et al.* [47] combined the HP filter with a dual-layer neural network. Herui *et al.* [48] paired the HP filter with an ARIMA model. Additional decomposition strategies appearing in the literature include singular value decomposition [49, 50] and wavelet transforms [51, 52].

Collectively, these works illustrate that decomposition-based hybrid models can markedly improve forecasting precision. Nevertheless, Brigato *et al.* [53] pointed out that no universal model fits every situation, underscoring the importance of strategic model design. The choice of decomposition technique is especially critical because each method possesses unique characteristics. Moving averages, for example, provide a straightforward means of separating trend and seasonality, although results hinge on the selected window length. STL performs iterative extraction of trend, seasonal, and remainder terms. EMD and wavelet decomposition decompose the demand series into multiple sub-components. However, producing an excessive number of sub-series can complicate the subsequent hybrid modeling process. Moreover, the forecasting algorithm assigned to each component must be compatible with its intrinsic properties; mismatched pairings may prevent accuracy gains even when employing sophisticated techniques.

Constructing a monthly electricity demand hybrid model in a multivariate context requires extensive socioeconomic, demographic, and meteorological inputs, with prediction quality directly tied to the accuracy of those future projections. At the same time, the persistent long-term trends and pronounced seasonal cycles inherent in monthly demand data add considerable complexity to model formulation. Long-run trends typically arise from gradual socioeconomic and demographic developments, whereas seasonal effects—largely weather-driven—are more volatile and difficult to represent precisely. To overcome these issues, the present study develops a univariate hybrid forecasting model grounded in a decomposition-integration paradigm. The HP filter is applied to split the demand series into a long-term trend and a seasonal component, thereby informing the selection of appropriate modeling tools. Given that socioeconomic forces mainly shape long-term trends and exhibit clear serial correlation, ARIMA is well positioned to model them through its autoregressive and moving-average components. By contrast, the seasonal portion shows greater variability and evident nonlinearity, rendering recurrent neural networks particularly suitable. Accordingly, ARIMA is used for trend forecasting, and RNNs for seasonal forecasting. The effectiveness of this approach is demonstrated through an application to total electricity consumption data from Guangzhou.

Materials and Methods

HP filter

The Hodrick-Prescott (HP) filter is a widely used technique for decomposing time series, enabling the separation of the long-run trend component from the cyclical (including seasonal) fluctuations in monthly electricity demand data, denoted as *Elect*. The following optimization problem gives its mathematical expression:

$$Elec_t = Trend_t + Cycle_t \quad (1)$$

Where $Trend_t$ denotes the extracted long-term trend, and $Cycle_t$ represents the isolated seasonal (cyclical) component. The HP filter carries out the decomposition by minimizing the loss function $Loss(t)$ given in Eq. 2, with the outcome controlled by the smoothing parameter λ , which is typically set to 14,400 for monthly data.

$$MinLoss(t) = \left\{ \sum_{t=1}^n (Elec_t - Trend_t)^2 + \lambda \sum_{t=1}^n \left[\frac{(Trend_{t+1} - Trend_t)^2}{-(Trend_t - Trend_{t-1})} \right]^2 \right\} \quad (2)$$

In contrast to EMD and STL methods, the HP filter decomposes electricity demand solely into trend and seasonal components. This approach reduces information loss and makes the follow-up modeling and analysis stages noticeably easier.

Autoregressive integrated moving average model

ARIMA is a widely used time-series forecasting method, written as $ARIMA(p, d, q)$. Here, p stands for the autoregressive order, d indicates the number of differencing operations needed to render the series stationary, and q corresponds to the moving average order, reflecting the impact of previous prediction errors. The ARIMA model is mathematically represented as follows:

$$\Delta^d y_t = c + \sum_{i=1}^p \varphi_i \Delta^d y_{t-i} + \sum_{j=1}^q \theta_j \varepsilon_{t-j} + \varepsilon_t \quad (3)$$

Where Δ stands for the differencing operator, y_t indicates the original time series, φ_i and θ_j denote the coefficients associated with the autoregressive and moving average components, respectively. ε_t is the white noise (error) term. When dealing with time series exhibiting clear seasonal behavior, the SARIMA extension is more appropriate.

ARIMA models remain a popular choice for forecasting electricity demand. While some studies indicate that a standalone ARIMA approach can yield lower performance than alternative techniques [54, 55], hybrid strategies that combine ARIMA with other methods often deliver improved predictive accuracy. For example, Royal et al. [56] merged ARIMA with a generalized additive model (GAM), whereas Büyükşahin and Ertekin [57] constructed hybrid models by pairing ARIMA with neural networks. Nie et al. [58] introduced an approach that integrates support vector machines (SVM) with ARIMA, and Wu et al. [59] presented a hybrid framework combining fractional ARIMA with an enhanced cuckoo search optimization algorithm. Given that the HP filter isolates the trend component by eliminating seasonality, and ARIMA excels at capturing serial correlations, the present study employs ARIMA to predict the long-term trend component. The most suitable orders p , d , and q are selected based on the Akaike information criterion (AIC).

Recurrent neural networks

Traditional neural networks are composed of an input layer, one or more hidden layers, and an output layer, with complete connections between consecutive layers but no connections within the same layer. Since time series data exhibit sequential dependencies, standard feedforward architectures such as backpropagation (BP) networks are generally regarded as inadequate for modeling them. In contrast to fully connected networks, recurrent neural networks (RNNs) explicitly account for temporal relationships via recurrent (feedback) connections, making them far more suitable for time-series modeling. Figure 1 outlines the fundamental mechanism of RNNs: the left panel shows a single recurrent unit, while the right panel displays its corresponding unfolded (temporally expanded) form. In Figure 1, X_t represents the input, O_t denotes the output, and h_t stands for the hidden state (which carries memory) at time step t , expressed as follows:

$$h_t = f(U * X_t + V * h_{t-1} + b) \quad (4)$$

Where $f(\cdot)$ stands for the activation function, most commonly selected as either sigmoid or tanh, and U and V represent the corresponding weight matrices. As a result, the hidden state effectively preserves temporal information from one time step to the next.

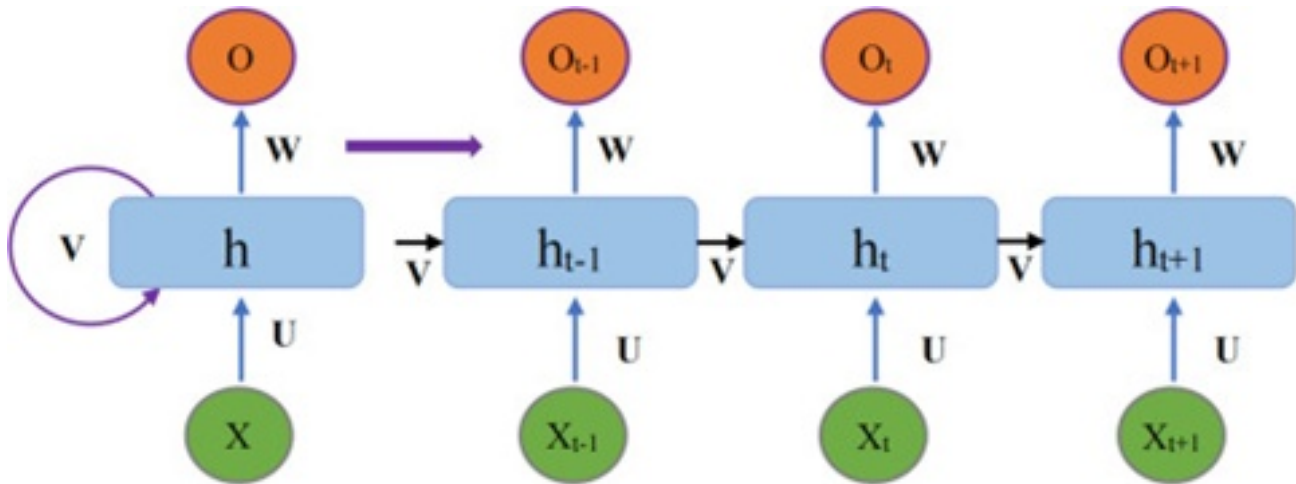


Figure 1. Schematic representation of recurrent neural networks (RNNs).

The layer corresponding to time step t depends strongly on the information processed at time $t-1$. The output produced by the neuron at time t , denoted as O_t , is given by the following expression:

$$O_t = g(W * h_t) \quad (5)$$

Where $g(\cdot)$ is used to denote the nonlinearity introduced via the activation function, and W corresponds to the matrix of weights linking to the output. Ordinarily, the parameter sets U , V , and W are held fixed and applied uniformly at every time step. Thanks to their ability to store past context, RNNs are particularly well-suited to time-series prediction.

Pavlatos *et al.* [60] conducted an extensive comparison of predictive performance between standard RNNs and gated recurrent units (GRUs) across diverse datasets, ultimately concluding that plain RNNs achieved more accurate results. Along similar lines, Çunkaş and Altun [61] found that RNNs delivered clearly better results than traditional backpropagation-based networks. The architecture has also found broad application inside composite forecasting systems. As one example, Ajitha *et al.* [62] proposed a combined RNN–LSTM architecture for predicting domestic electricity usage. Yan *et al.* [63] proposed a multi-level RNN architecture that separates a series into trend, seasonal, and irregular components, models each segment individually with RNNs, and recombines them to obtain the complete forecast. Hussein and Awad [64] developed an integrated technique that pairs RNNs with evolutionary (genetic) optimization to enhance load-forecasting precision. For these reasons, the present research adopts RNNs to model and project the seasonal patterns separated by the HP filter.

Implementation in this work relies on the Keras library to construct a stacked, two-layer RNN. Each of the two recurrent layers contains 24 SimpleRNN units, after which a single-unit Dense layer produces the final scalar prediction. Training uses the Adam optimizer with a learning rate of 0.001, and mean squared error (MSE) is the objective function. Optimization proceeds via mini-batch gradient descent with a batch size of 5 for 35 epochs. The results obtained verify that the architecture successfully learns and reproduces the time-dependent behavior of the seasonal series.

Assessment of predictive accuracy

Final electricity demand estimates are produced by aggregating the separately forecasted trend and seasonal signals. **Figure 2** depicts the complete processing pipeline of the suggested hybrid prediction system.

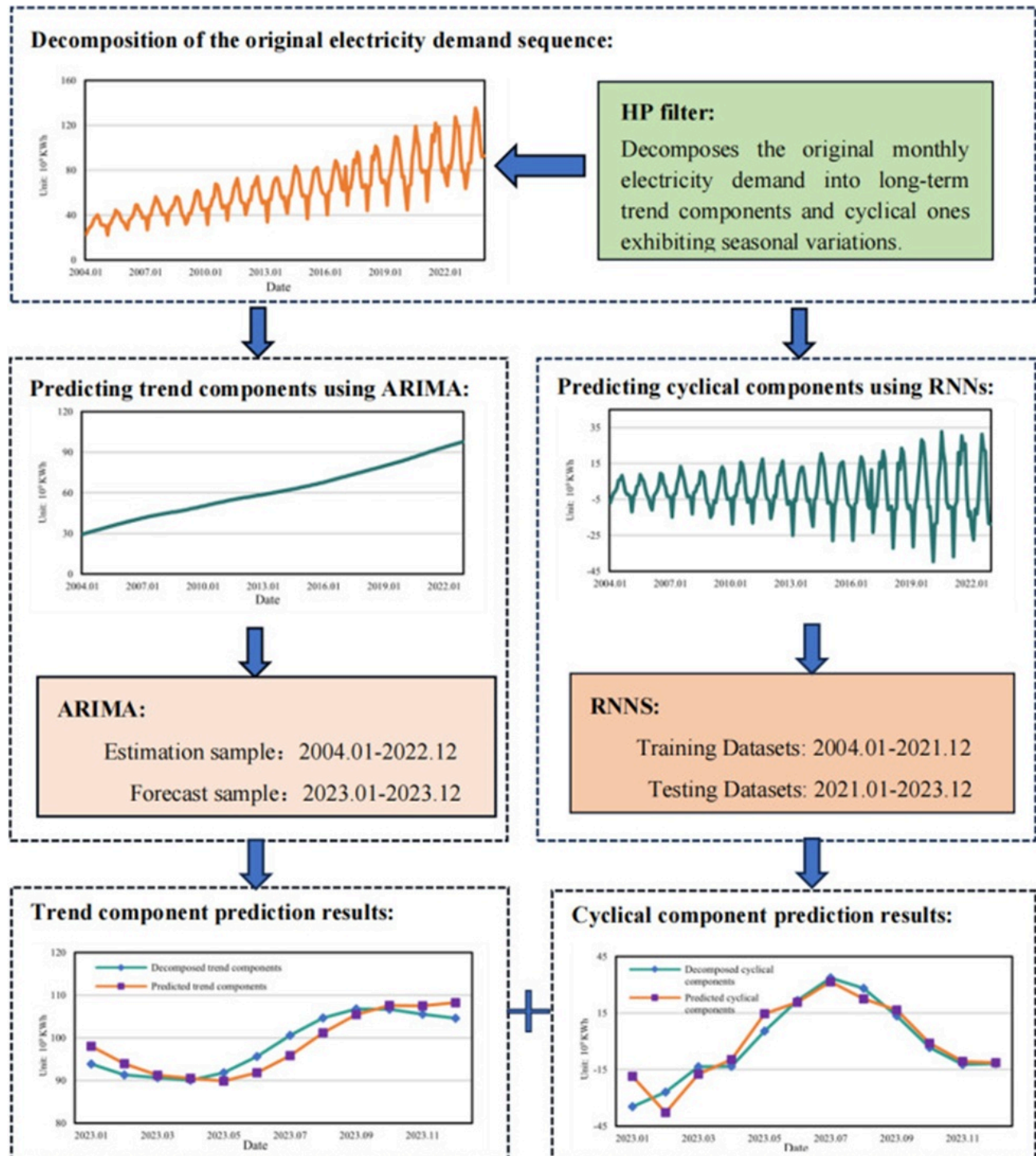


Figure 2. Overall architecture of the hybrid forecasting approach that integrates the Hodrick-Prescott filter, recurrent neural networks, and the autoregressive integrated moving average model.

Forecasting performance is routinely judged using indicators such as mean absolute percentage error (MAPE), root mean square error (RMSE), mean absolute error (MAE), and R-squared (R^2) [39]. That said, some authors argue that Willmott's index (WI) and the Legates–McCabe index (LMI) provide more reliable measures of model–data agreement than R^2 in many situations [9, 14]. Accordingly, the effectiveness of the hybrid model developed here is quantified using the set of performance measures given in Eqs. 6–10.

$$\text{MAPE} = \frac{100\%}{n} \sum_{i=1}^n \left| \frac{\hat{y}_i - y_i}{y_i} \right| \quad (6)$$

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^n (\hat{y}_i - y_i)^2}{n}} \quad (7)$$

$$\text{MAE} = \frac{\sum_{i=1}^n |\hat{y}_i - y_i|}{n} \quad (8)$$

$$\text{WI} = 1 - \frac{\sum_{i=1}^n (\hat{y}_i - y_i)^2}{\sum_{i=1}^n (|\hat{y}_i - \bar{y}| + |y_i - \bar{y}|)^2} \quad (9)$$

$$\text{LMI} = 1 - \frac{\sum_{i=1}^n |\hat{y}_i - y_i|}{\sum_{i=1}^n |y_i - \bar{y}|} \quad (10)$$

Where $\hat{y}_i$ and y_i stand for the forecasted and the true observed values, respectively, $\bar{y}$ indicates the average of the observed values, and n corresponds to the total count of predicted observations.

Experiments and Results

Dataset

Monthly records of electricity usage in Guangzhou, China, covering the period from January 2004 through December 2023, sourced from the Guangzhou Municipal Bureau of Statistics, were used to test the effectiveness of the suggested hybrid forecasting model. The full dataset was divided into a training subset spanning January 2004 to December 2022 and a testing subset covering January 2023 to December 2023.

Figure 3 illustrates the pattern of electricity usage in Guangzhou, showing a consistent long-term rise accompanied by regular seasonal cycles. Usage levels typically reach their minimum in February and peak in July. The combination of sustained growth and recurring seasonal swings makes this dataset particularly well-suited for HP-filter-based separation and analysis.

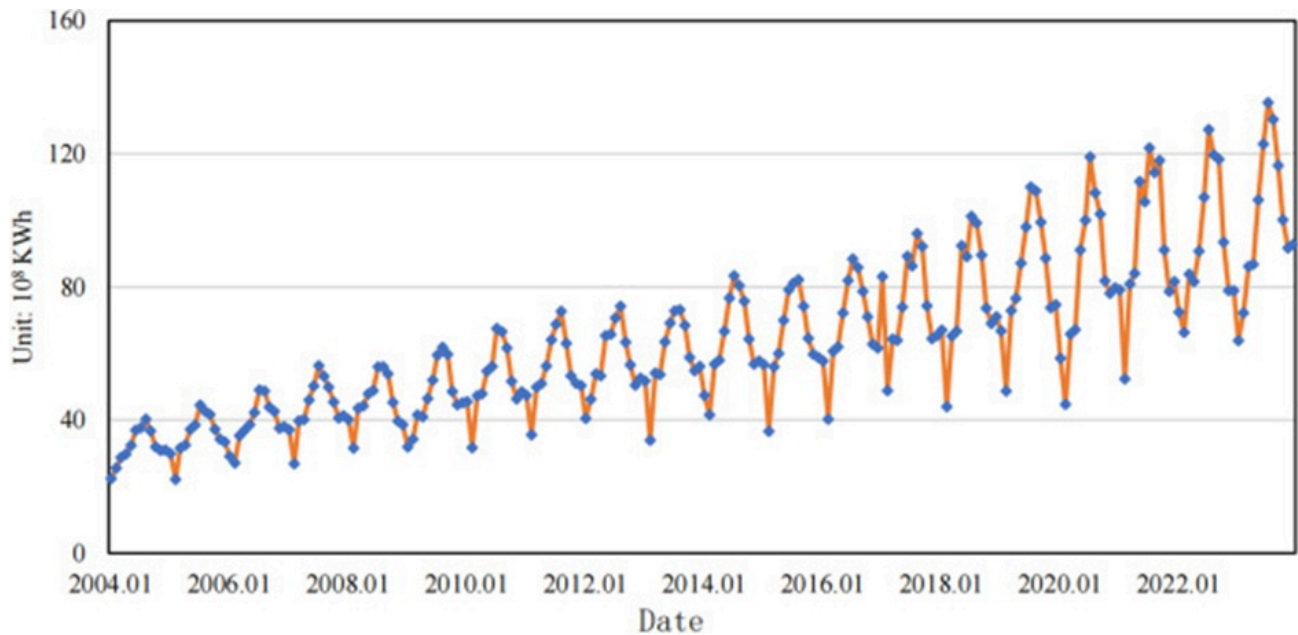


Figure 3. Overall electricity usage in Guangzhou, China, over the period January 2004 to December 2023.

Results of the HP filter

Implementing the HP filter on the raw electricity consumption series effectively isolates the underlying long-term trend from the recurring seasonal movements (Figure 4). The resulting trend shows a smoother, continuous increase over time. In contrast, the separated seasonal component clearly reveals recurring cycles free of any overarching trend effects. Such separation enables forecasting techniques to better account for the distinct behaviors of each part, ultimately leading to more precise predictions.

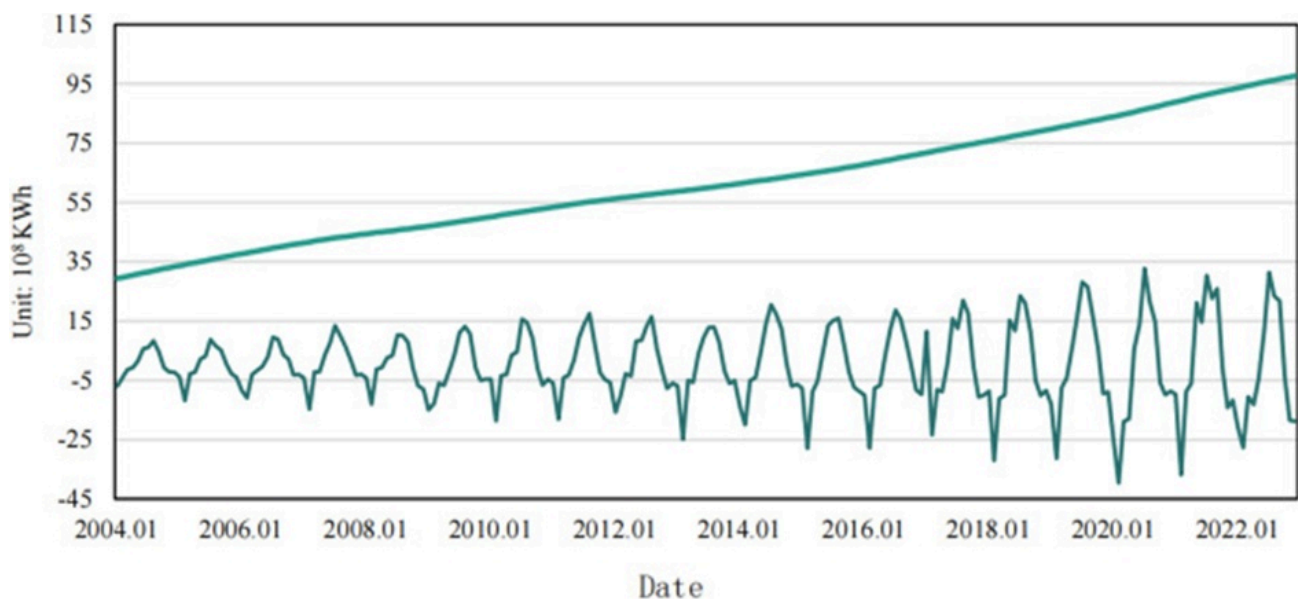


Figure 4. Trend and cyclical elements of total electricity usage in Guangzhou from January 2004 to December 2023, obtained through HP filter decomposition.

Trend component prediction results

An ARIMA model was fitted to the trend data from January 2004 to December 2022, with the most suitable parameters selected using the Akaike Information Criterion (AIC). After applying a log transformation and second differencing to ensure stationarity, the preferred specification emerged as ARIMA(4, 2, 3). One-step-ahead rolling predictions for the period January to December 2023 (Figure 5) indicate excellent alignment with the actual decomposed trend.

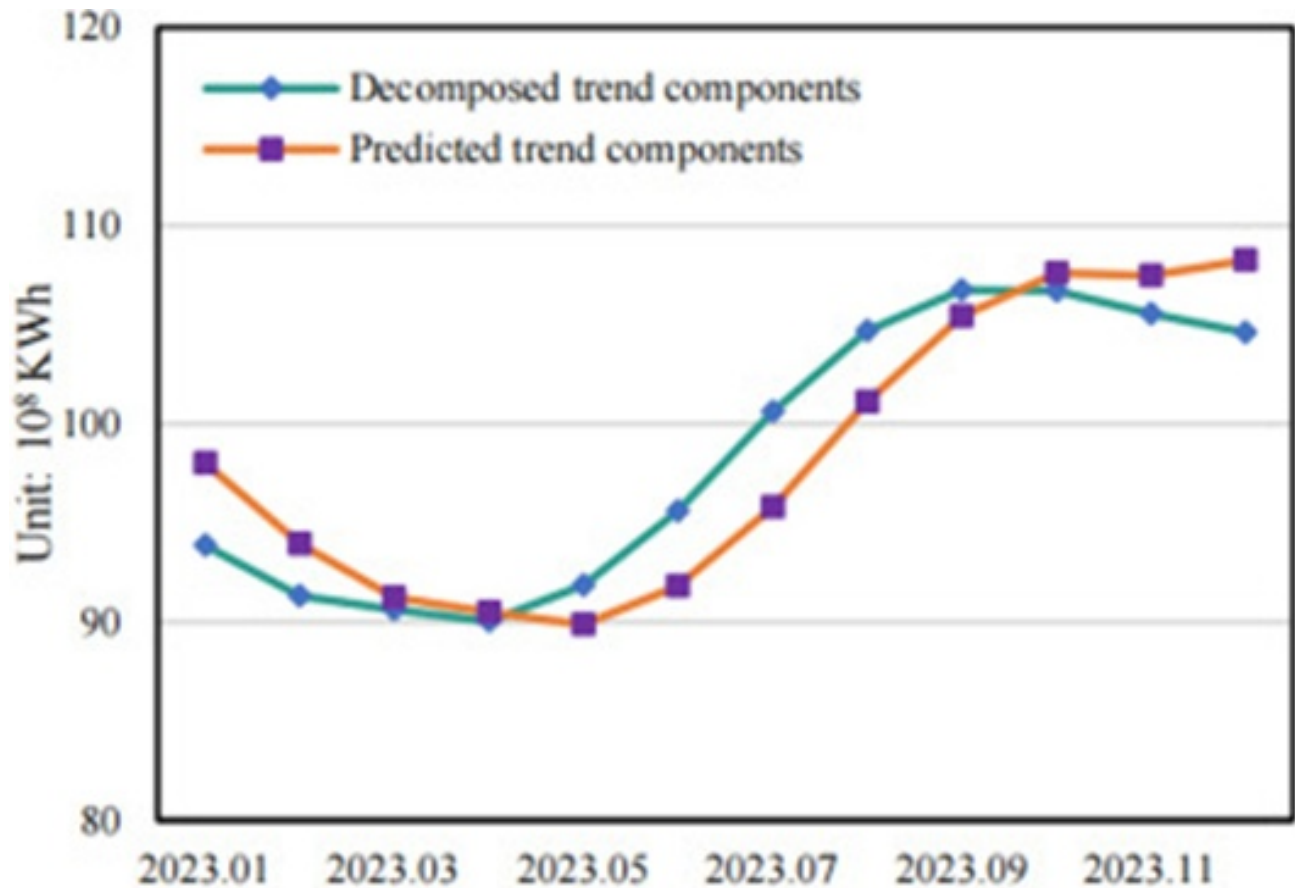


Figure 5. Forecasted trend element of total electricity usage in Guangzhou for January 2023 to December 2023.

Periodic component prediction results

The isolated seasonal series exhibits pronounced cyclical behavior that mirrors patterns in the raw demand data, with the lowest consumption typically in February and the highest in August or September. Notably, the magnitudes of fluctuations have increased over the years, suggesting increasing variance (heteroscedasticity) in the series.

For RNN-based modeling of these seasonal elements, the training window used data from January 2004 to December 2021, with testing performed on January 2020 to December 2023. A sliding input sequence of 24 months was employed to predict the value for the subsequent (25th) month. As shown in Figure 6, the RNN predictions closely track the actual seasonal variations.

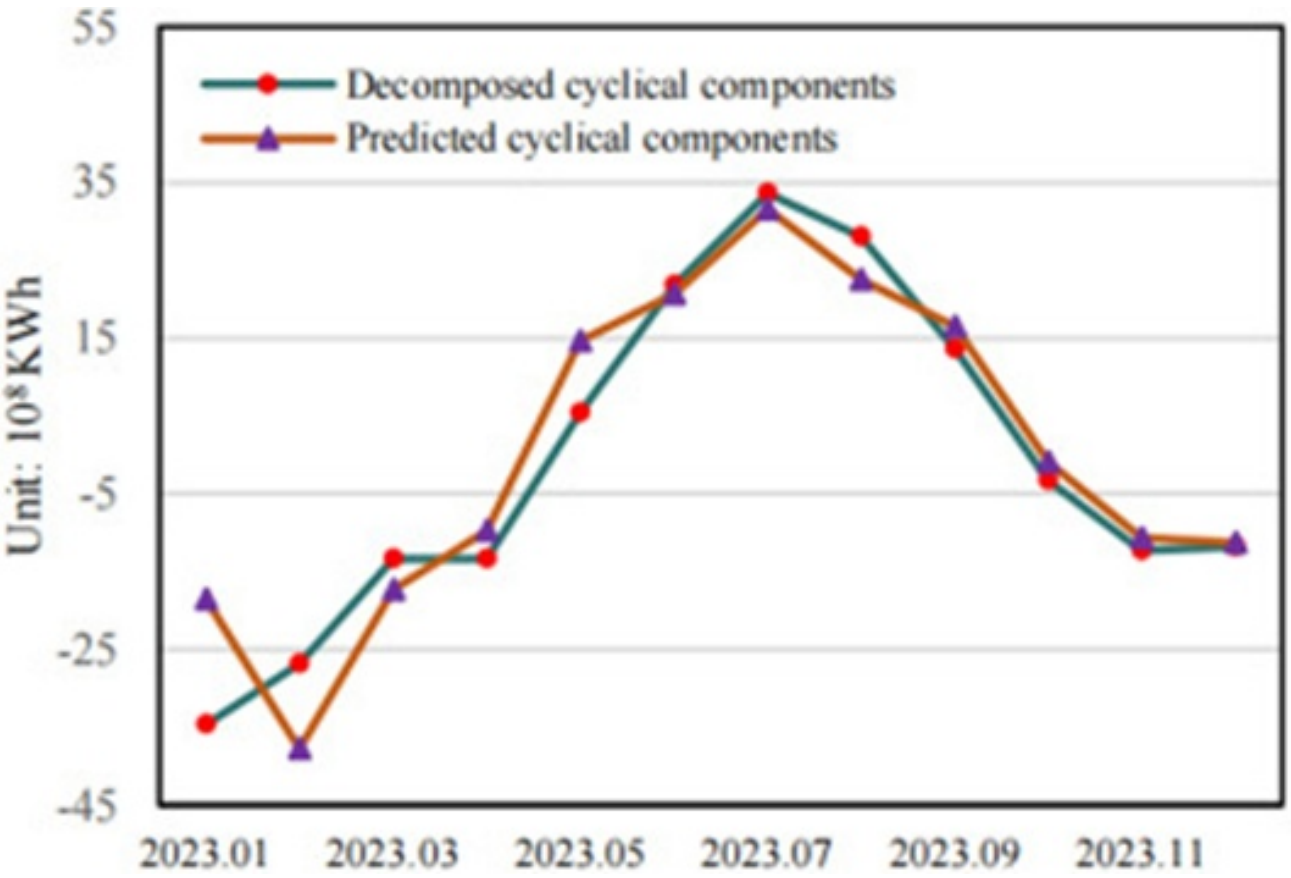


Figure 6. Forecasted cyclical element of total electricity usage in Guangzhou for January 2023 to December 2023.

Comparison of predictive accuracy

The complete electricity demand forecast results from adding the separately predicted trend and seasonal parts. **Figure 7** compares the reconstructed predictions with the observed values for January to December 2023, revealing close correspondence and thereby validating the reliability and strength of the proposed hybrid method.

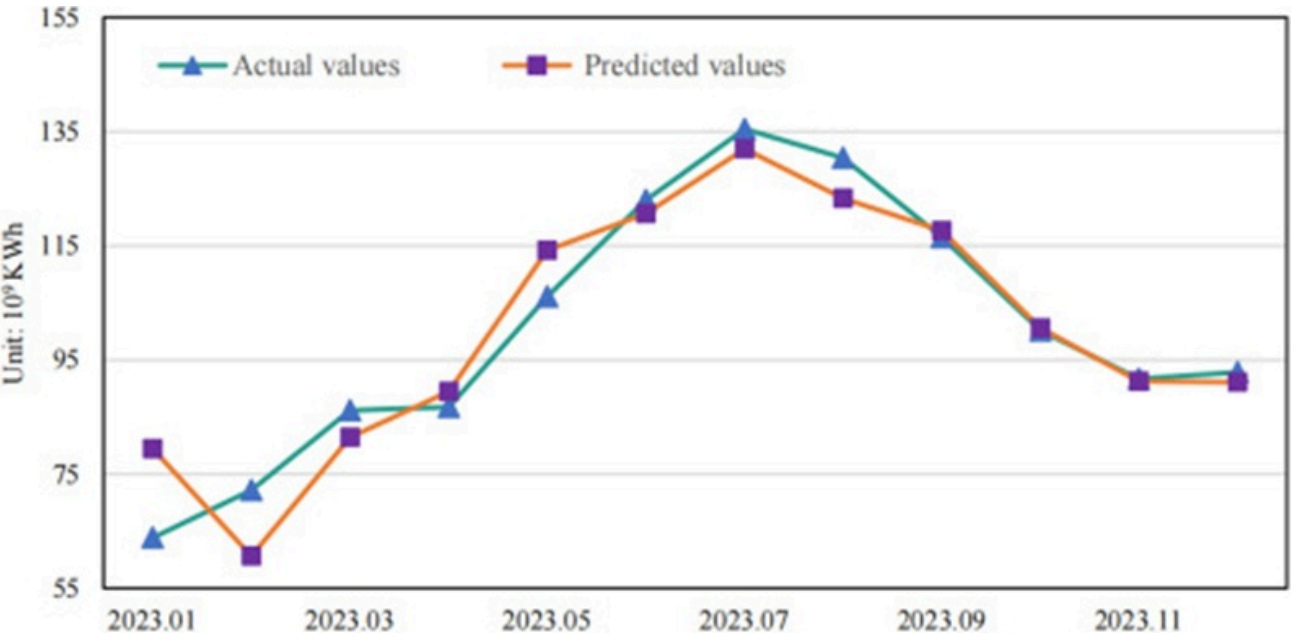


Figure 7. Reconstructed final forecast of total electricity consumption in Guangzhou, China, for January to December 2023, based on combined trend and cyclical component predictions.

Benchmark against standard time series techniques

To more rigorously demonstrate the advantage of the newly developed hybrid approach in terms of forecast quality, its performance is compared with several well-established univariate forecasting procedures: additive Holt-Winters (ADDHW), multiplicative Holt-Winters (MULHW), the ETS framework, and SARIMA. Throughout the discussion, the present method is referred to as HP_RNN_ARIMA for brevity.

Figure 8 displays the month-by-month forecast trajectories produced by each technique over January–December 2023. A clear pattern emerges: virtually every model shows notably larger deviations in January and February. The principal cause is the variable timing of the Chinese Spring Festival (a major moving holiday), which can fall anywhere within those two months depending on the lunar calendar. This celebration triggers widespread changes in industrial activity, commercial operations, and household routines, leading to irregular and pronounced swings in electricity load that are notoriously hard to model accurately.

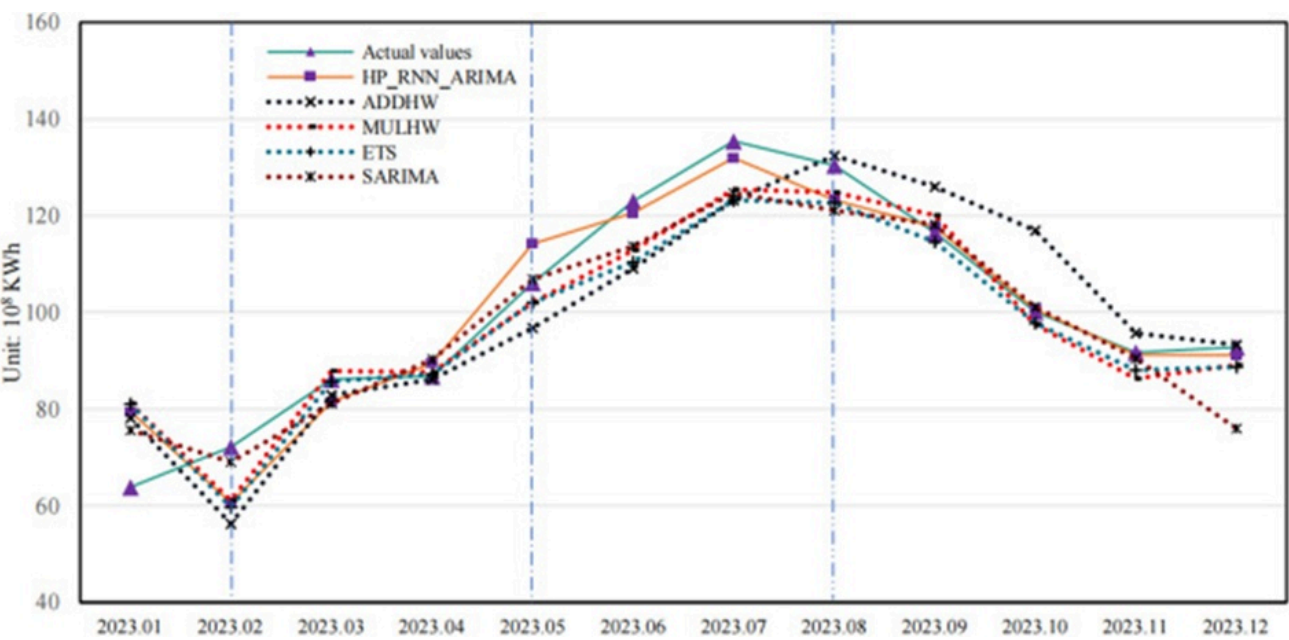


Figure 8. Visual comparison of forecasts generated by the hybrid HP_RNN_ARIMA model (this study) versus classical time series methods—ADDHW, MULHW, ETS, and SARIMA—for monthly electricity demand in Guangzhou, China, during 2023.

A second challenging window spans May through August, corresponding to the peak summer period. Demand in these months is heavily shaped by ambient weather—especially temperature swings—which drive substantial and sometimes abrupt shifts in consumption. Accurate prediction becomes considerably more difficult under such variable conditions. Here, the hybrid HP_RNN_ARIMA stands out, delivering clearly tighter predictions than the traditional counterparts during the summer months. In the remaining periods (March–April and September–December), predictive quality is generally good across most methods (with ADDHW as the notable exception), yet HP_RNN_ARIMA maintains the smallest discrepancies throughout.

Table 1 compiles the numerical results obtained from three error statistics and two agreement indices for all competing approaches. Across all accuracy measures, the proposed HP_RNN_ARIMA achieves the lowest values, outperforming the classical baselines. The relative error reductions are substantial: MAPE drops by 9.70% to 35.66%, RMSE by 14.18%

to 35.06%, and MAE by 20.01% to 41.92%. Turning to fit quality, HP_RNN_ARIMA posts the best WI and LMI scores. Improvements over the conventional models range from 0.0125 to 0.0349 for WI and from 0.0923 to 0.2206 for LMI.

Table 1. Summary of predictive performance: HP_RNN_ARIMA compared with ADDHW, MULHW, ETS, and SARIMA using MAPE, RMSE, MAE, WI, and LMI metrics.

Model	MAPE (%)	Reduction in MAPE	RMSE (10 ⁸ kWh)	Reduction in RMSE	MAE (10 ⁸ kWh)	Reduction in MAE	WI	WI Gain	LMI	LMI Gain
ADDHW	9.13	35.66 %	10.38	35.06 %	8.54	41.92 %	0.9389	0.0349	0.5316	0.2206
MULHW	7.06	16.84 %	7.85	14.18 %	6.34	21.77 %	0.9613	0.0125	0.6522	0.1000
ETS	7.24	18.84 %	8.56	21.26 %	6.61	25.00 %	0.9522	0.0216	0.6372	0.1150
ARIMA	6.50	9.70 %	7.99	15.71 %	6.20	20.01 %	0.9597	0.0141	0.6599	0.0923
HP_RNN_ARIMA (proposed)	5.87	—	6.74	—	4.96	—	0.9738	—	0.7522	—

Benchmark against standalone neural architectures

The analysis then shifts to comparing the proposed hybrid with pure neural-network forecasters—namely, BP networks, plain RNNs, and LSTM units. Identical hyperparameters (number of neurons, look-back window length, training/testing partition) were deliberately preserved across all neural-based runs to guarantee equitable evaluation.

Figure 9 juxtaposes the error profiles of HP_RNN_ARIMA against those of the individual neural models. The graphs highlight a systematic tendency among standalone networks—especially BP—to systematically under-forecast actual consumption. Except for the holiday-affected January–February interval, the hybrid method produces consistently smaller deviations and performs particularly well during periods of elevated demand.

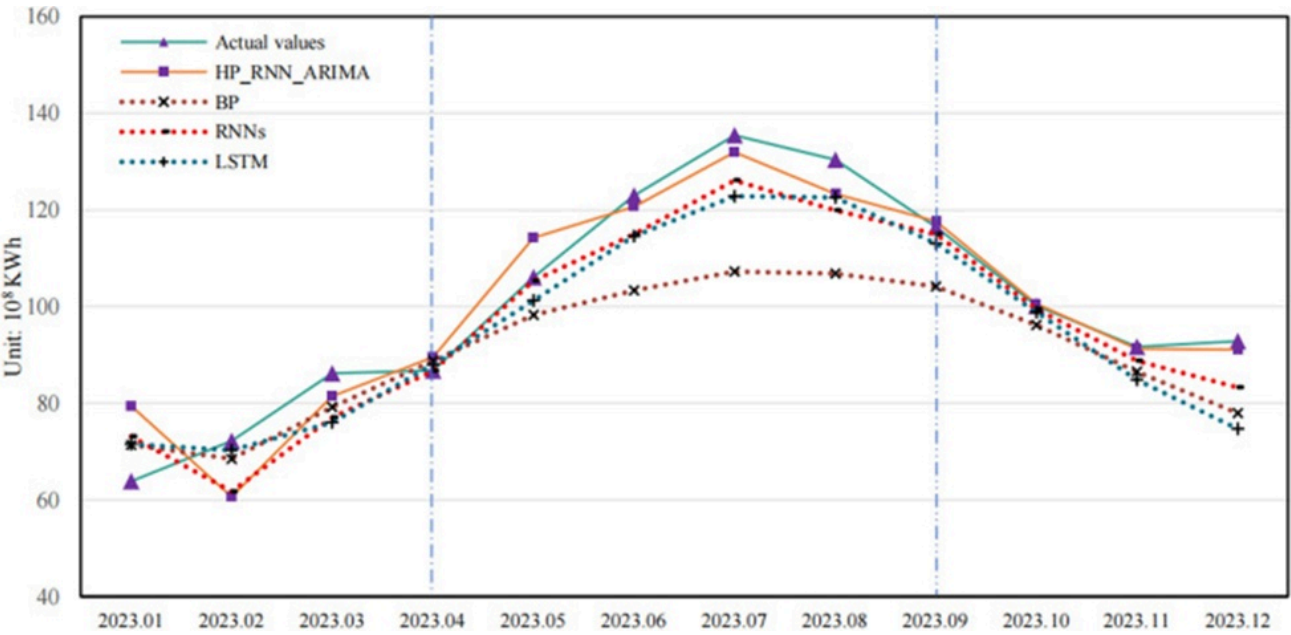


Figure 9. Head-to-head comparison of electricity demand forecasts in Guangzhou (Jan–Dec 2023) produced by the hybrid HP_RNN_ARIMA versus standalone neural predictors (BP, RNNs, LSTM).

Table 2 lists the quantitative forecasting outcomes when single neural architectures are applied directly to the raw demand series. These numbers reinforce the clear edge held by HP_RNN_ARIMA, which records the smallest MAPE, RMSE, and MAE among all neural contenders. The measured accuracy gains are: MAPE reduced by 9.05% to 44.02%, RMSE reduced by 20.88% to 51.74%, and MAE reduced by 29.53% to 56.23%.

Table 2. Performance metrics for HP_RNN_ARIMA versus individual neural models (BP, RNNs, LSTM) evaluated through MAPE, RMSE, MAE, WI, and LMI.

Model	MAPE (%)	MAPE reduction (%)	RMSE (10 ⁸ kWh)	RMSE reduction (%)	MAE (10 ⁸ kWh)	MAE reduction (%)	WI	WI improvement	LMI	LMI improvement
BP	10.49	44.02	13.96	51.74	11.33	56.23	0.8485	0.1253	0.3785	0.37
RNNs	6.46	9.05	8.81	23.54	7.10	30.16	0.9683	0.0055	0.6691	0.08
LSTM	7.16	17.94	8.52	20.88	7.04	29.53	0.9561	0.0177	0.6140	0.13
HP_RNN_ARIMA (proposed)	5.87	—	6.74	—	4.96	—	0.9738	—	0.7522	—

Additionally, HP_RNN_ARIMA achieves superior WI and LMI values relative to every standalone neural baseline. Specific improvements over BP, RNNs, and LSTM are +0.1253, +0.0055, and +0.0177 for WI, and +0.3737, +0.0831, and +0.1382 for LMI, respectively.

Taken together, **Tables 2 and 3** indicate that conventional statistical time series models sometimes deliver better results than neural-only approaches in selected scenarios. Notably, MULHW attains an MAPE of 7.06 %, which beats both LSTM (7.16 %) and BP (10.49 %). This pattern is consistent with earlier literature, which concludes that forecasting superiority is context-dependent and that no single family of models dominates universally [53].

Table 3. Predictive performance comparison: HP_RNN_ARIMA versus BP_DEC, RNN_DEC, and LSTM_DEC according to MAPE, RMSE, MAE, WI, and LMI.

Model	MAPE (%)	MAPE reduction (%)	RMSE (10 ⁸ kWh)	RMSE reduction (%)	MAE (10 ⁸ kWh)	MAE reduction (%)	WI	WI gain	LMI	LMI gain
BP_DEC	8.82	33.39	10.64	36.67	8.99	44.87	0.9273	0.0465	0.5065	0.2457
RNN_DEC	6.09	3.60	7.04	4.27	5.19	4.43	0.9715	0.0023	0.7153	0.0369
LSTM_DEC	6.45	8.96	7.21	6.47	5.35	7.27	0.9672	0.0066	0.7066	0.0456
HP_RNN_ARIMA (proposed)	5.87	—	6.74	—	4.96	—	0.9738	—	0.7522	—

Comparison with other hybrid models

In the final stage of evaluation, multiple hybrid forecasting strategies built around the HP filter were constructed using different component-modeling choices and then directly contrasted with HP_RNN_ARIMA. Each alternative follows the same initial decomposition step via HP filter, after which both the trend and the seasonal/cyclical parts are predicted using one unified neural architecture—either BP, RNNs, or LSTMs—labeled BP_DEC, RNN_DEC, and LSTM_DEC accordingly.

Figure 10 illustrates the month-by-month forecast profiles for HP_RNN_ARIMA alongside these competing hybrid variants. Among them, BP_DEC shows the poorest overall behavior, systematically producing values below the actual observations. LSTM_DEC, in particular, exhibits a clear tendency to overestimate demand from January through July—the period when electricity usage normally climbs. RNN_DEC produces results that are fairly close to those of HP_RNN_ARIMA, though it often falls slightly short of actual levels, resulting in modestly lower precision than the proposed approach.

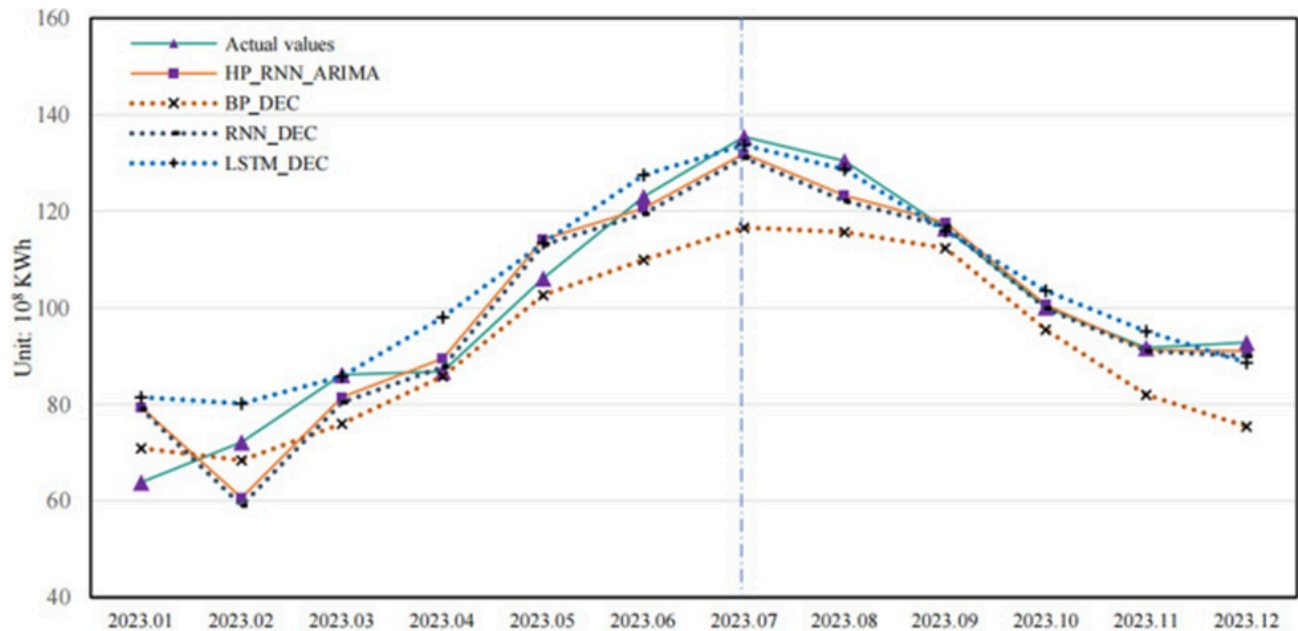


Figure 10. Comparative forecast trajectories for the proposed HP_RNN_ARIMA hybrid model versus other HP-filter-based hybrids (BP_DEC, RNN_DEC, LSTM_DEC) in forecasting Guangzhou electricity demand, January–December 2023.

Table 3 reports the quantitative performance of all HP-filter-based hybrid configurations, confirming that HP_RNN_ARIMA delivers the smallest errors across the board. Relative to BP_DEC, RNN_DEC, and LSTM_DEC, it achieves MAPE reductions of 3.6% to 33.39%, RMSE reductions of 4.27% to 36.67%, and MAE reductions of 4.43% to 44.87%. Improvements in fit metrics are also evident: WI rises by 0.0465, 0.0023, and 0.0066, while LMI rises by 0.2457, 0.0369, and 0.0456, respectively. These patterns reinforce the conclusion that ARIMA excels at modeling the persistent long-run movement in demand, whereas RNNs are better than BP or LSTM at representing repeating cyclic behavior.

Cross-referencing **Tables 2 and 3** highlights the clear benefit of first decomposing the raw demand series with the HP filter before applying neural techniques. For example, the standalone BP network produces MAPE, RMSE, and MAE of 10.49%, 13.96%, and 11.33%, respectively. When the same BP architecture is applied after HP decomposition (BP_DEC), the figures drop to 8.82%, 10.64%, and 8.99%, resulting in error reductions of 15.92%, 23.80%, and 20.60%.

Likewise, RNN_DEC cuts MAPE, RMSE, and MAE by 5.65%, 20.14%, and 26.93% relative to plain RNN, and LSTM_DEC achieves reductions of 9.87%, 15.40%, and 24.00% relative to standalone LSTM. Thus, separating the series into trend and cyclical components via HP filtering enables neural predictors to focus more sharply on the specific dynamics of each component, greatly reducing the confounding effects of mixed long-term and periodic signals and markedly boosting overall forecast quality.

Taken together, comparisons across diverse forecasting strategies show that HP_RNN_ARIMA consistently records the lowest MAPE, RMSE, and MAE while attaining the highest WI and LMI values, thereby establishing its clear advantage in both accuracy and reliability.

Across the full set of benchmarks, the proposed method lowers MAPE errors by roughly 3.6% to 44.02% (Figure 11), RMSE errors by approximately 4.27% to 51.74% (Figure 12), and MAE errors by about 4.43% to 56.23% (Figure 13). In Figures 11–13: PFEI represents the percentage decrease in forecasting error relative to the best-performing HP_RNN_ARIMA model (negative values indicate a reduction in forecasting error). For fit-quality indices, WI gains range from roughly 0.0023 to 0.1253 (Figure 14), and LMI gains range from about 0.0369 to 0.3737 (Figure 15).

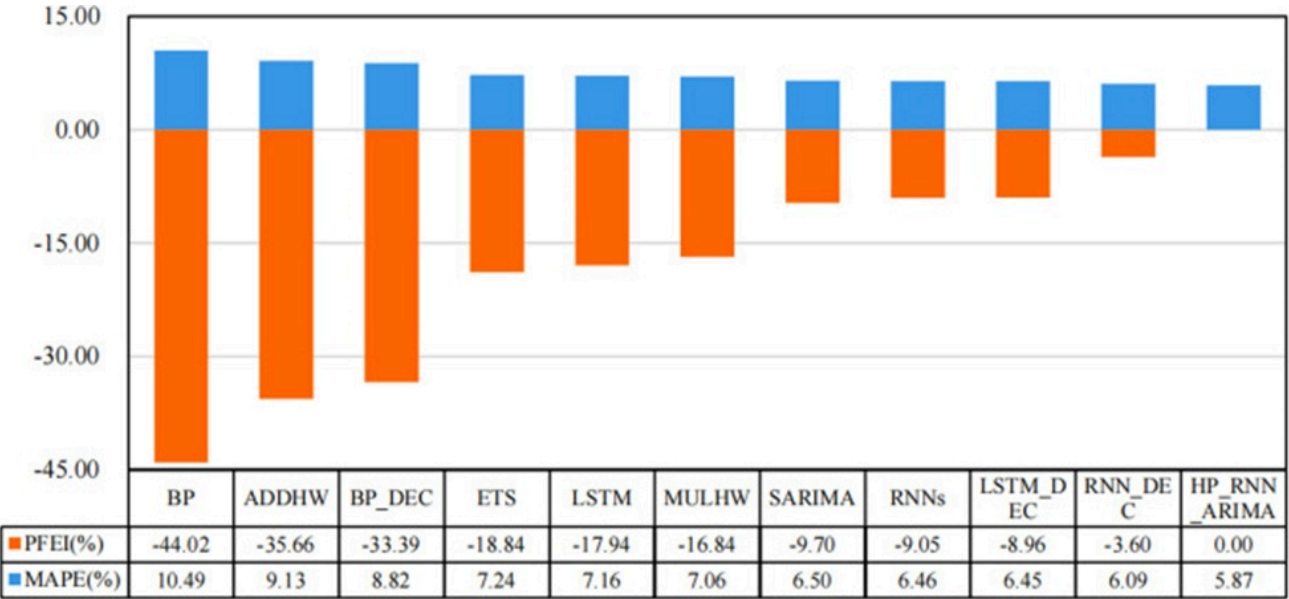


Figure 11. MAPE values across the evaluated forecasting models together with percentage error reduction (PFEI) relative to HP_RNN_ARIMA. Negative PFEI values signify lower error.

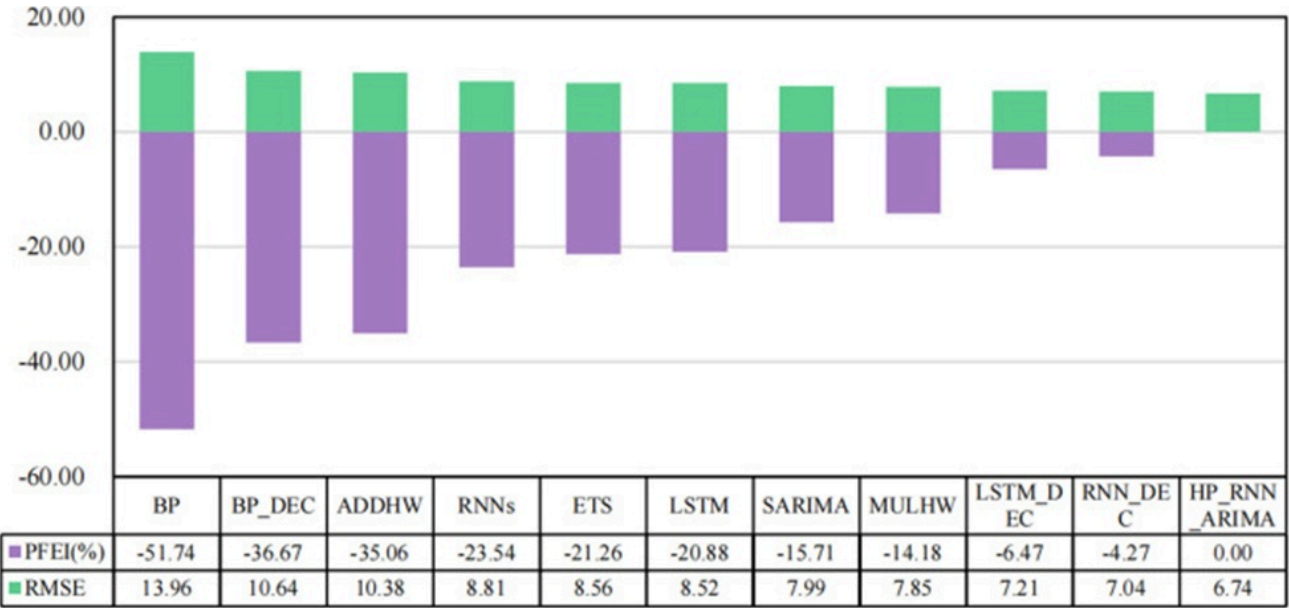


Figure 12. RMSE values across the evaluated forecasting models together with percentage error reduction (PFEI) relative to HP_RNN_ARIMA. Negative PFEI values signify lower error.



Figure 13. MAE values across the evaluated forecasting models together with percentage error reduction (PFEI) relative to HP_RNN_ARIMA. Negative PFEI values signify lower error.

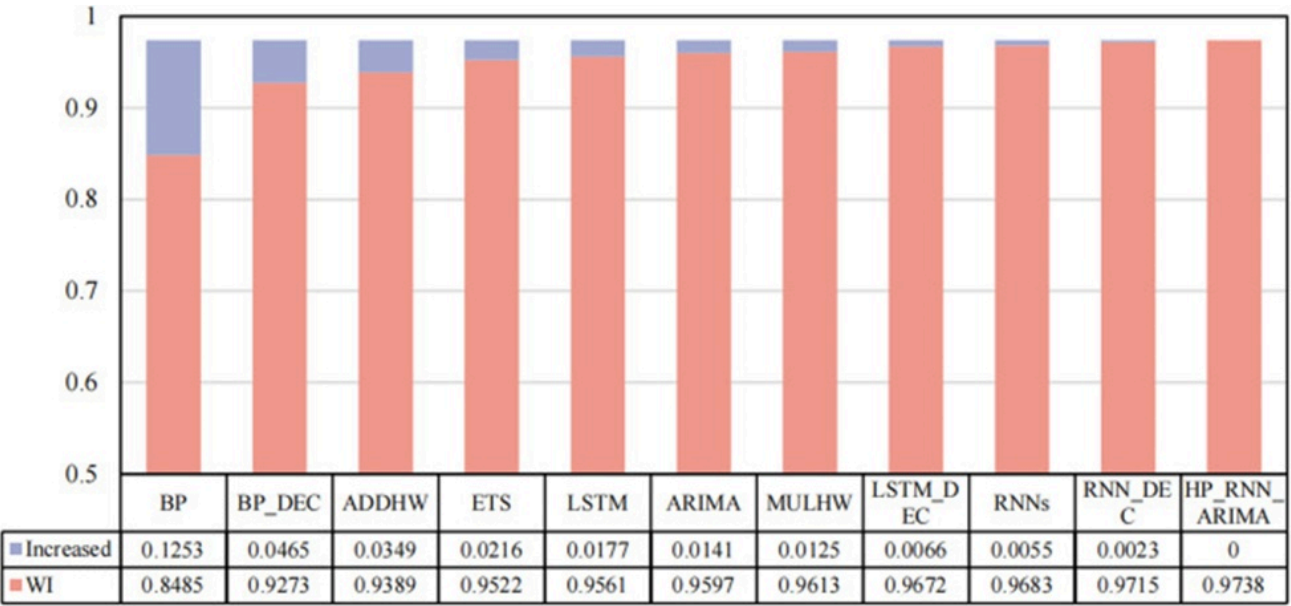


Figure 14. WI goodness-of-fit scores for the different models and corresponding improvement potential relative to the leading HP_RNN_ARIMA model.

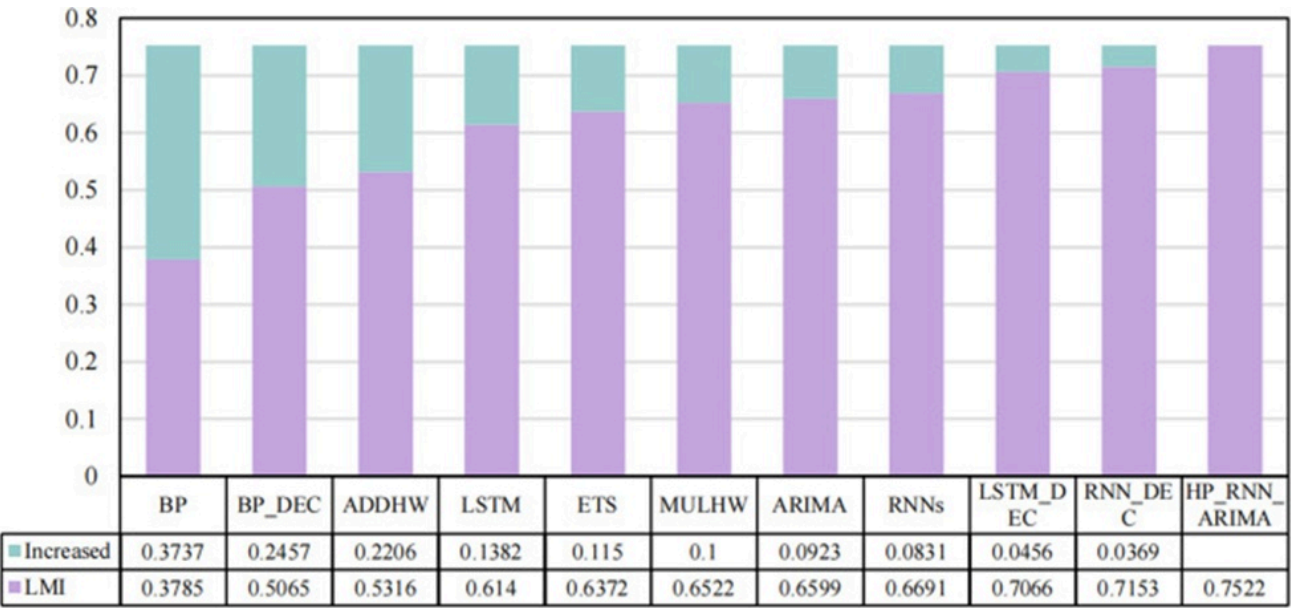


Figure 15. LMI goodness-of-fit scores for the different models and corresponding improvement potential relative to the leading HP_RNN_ARIMA model.

HP_RNN_ARIMA, together with RNN_DEC and LSTM_DEC, ranks at the top across all error metrics (MAPE, RMSE, MAE) and both fit indices (WI, LMI), demonstrating consistently robust and dependable results. By contrast, the remaining models exhibit more variable performance across metrics, reflecting comparatively lower robustness. These outcomes emphasize the substantial value added by HP-filter decomposition in time series analysis.

Conclusion

The present research introduces a straightforward univariate forecasting strategy that begins by decomposing monthly electricity consumption into long-term trend and cyclical (seasonal) elements using the HP filter. Separate ARIMA and RNN models are then applied to predict each component, and the final demand estimate is obtained by combining the two forecasts. The approach was empirically tested on Guangzhou’s monthly electricity consumption records covering January 2004 to December 2023.

Experimental findings demonstrate that this hybrid framework outperforms a range of established methods—including Holt-Winters variants, standalone ARIMA/ETS models, individual neural architectures (BP, RNNs, LSTM), and their HP-filter-based hybrid counterparts. Decomposing the series into components with distinct dynamic behaviors via HP filtering effectively reduces confusion caused by superimposed trend and cyclical signals, leading to noticeably higher predictive precision.

A central strength of the proposed model lies in its deliberate pairing of modeling tools with the specific characteristics of each decomposed series: ARIMA performs particularly well at tracking sustained directional movement in electricity demand. At the same time, RNNs excel at capturing recurring seasonal oscillations. Merging classical statistical techniques with modern recurrent neural networks yields meaningful gains in forecast quality.

The resulting hybrid model is computationally lightweight, straightforward to deploy, and operates effectively with only univariate historical series, making it readily adaptable to routine planning tools used by electricity suppliers, transmission system operators, and large-scale consumers. It thereby provides dependable guidance for operational scheduling, resource allocation, and participation in electricity markets.

Importantly, because the method relies solely on past demand observations within a univariate framework, it requires no supplementary socioeconomic or external indicators. Its main constraint, however, is the inability to incorporate drivers such as macroeconomic expansion, population changes, or evolving climate patterns—factors that could limit its applicability for long-range energy policy analysis. Furthermore, although extreme weather events and potential climate-induced demand shifts have received growing attention, the current univariate setup does not explicitly model such influences. Future extensions will therefore aim to integrate relevant socioeconomic, demographic, and meteorological variables, thereby advancing toward more comprehensive multivariate forecasting frameworks.

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Conflict of interest

None

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Ethics statement

None

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