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# Improving Monthly Electricity Demand Forecasts through HP Filter Decomposition and Hybrid ARIMA-RNN Modeling

Ethan Marshall[1], Noor Al-Harbi[2*], Kevin Brooks[3]

## Abstract

The presence of both long-term growth patterns and recurring seasonal changes in monthly electricity demand creates notable obstacles for reliable prediction. This research therefore develops a single-variable time series method that applies the Hodrick-Prescott (HP) filter to split the demand data into trend and seasonal parts. Autoregressive integrated moving average (ARIMA) forecasts the trend part, while recurrent neural networks (RNNs) manage the periodic part. Final predictions result from merging the two separate forecasts. Performance testing relies on Guangzhou's complete electricity usage statistics. Against standard techniques like Holt-Winters, Seasonal ARIMA, and error-trend-seasonal (ETS), the suggested HP_RNN_ARIMA hybrid model cuts mean absolute percentage error (MAPE), root mean square error (RMSE), and mean absolute error (MAE) by about 9.70 % to 35.66 %, 14.18 % to 35.06 %, and 20.01 % to 41.92 %, respectively. Versus separate neural networks including backpropagation (BP), RNNs, and long short-term memory (LSTM), the model lowers MAPE, RMSE, and MAE by roughly 9.05 % to 44.02 %, 20.88 % to 51.74 %, and 29.53 % to 56.23 %, respectively. In relation to additional hybrid models, reductions reach 3.60 % to 33.39 %, 4.27 % to 36.67 %, and 4.43 % to 44.87 %. The model also records the top Willmott's index (WI) and Legates and McCabe's index (LMI) results, demonstrating enhanced model reliability. Besides this, breaking down the series with the HP filter and predicting components independently yields substantial improvements in forecast quality.

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

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## Introduction

Effective load prediction remains essential for strategic energy decisions, power network planning, and daily utility operations, playing a central role in maintaining the security, reliability, and operational performance of electricity systems [1]. As the worldwide movement toward low-carbon energy systems continues, sources such as solar and wind are growing rapidly, raising important questions about network reliability. Lately, economic progress and shifts in weather patterns have significantly amplified fluctuations in electricity consumption. Greater renewable penetration in grids and heightened demand swings underscore the need for robust forecasting capabilities.

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Forecasting electricity demand is usually grouped according to timeframe: long-term (5 to 10 years), medium-term (1 month to 5 years), and short-term (1 h to 1 week) [2]. The majority of existing work has prioritized short-term forecasts, offering only modest coverage of medium- and long-term electricity demand estimation [3]. Monthly electricity demand forecasting is considered a medium-term forecast. These series commonly feature ongoing expansion and seasonal movements, where the joint effect of both factors increases the difficulty of creating accurate models [4].

To improve the quality of monthly electricity demand predictions, the current study proposes a combined model that combines the Hodrick-Prescott (HP) filter, the autoregressive integrated moving-average (ARIMA) model, and recurrent neural networks (RNNs). Initially, the HP filter decomposes the demand series into a long-term trend component and a seasonal component. ARIMA then predicts the trend component, while RNNs address the seasonal component. These separate results are joined afterward to create the complete forecast. The essential traits and strengths of the suggested hybrid model are listed here.

First, the HP filter clearly separates extended trends from seasonal cycles, making it easier to pick fitting techniques for each element while limiting cross-influence throughout the modeling stage. Unlike procedures that fragment the full series into numerous segments, the HP filter produces only two components: trend and cyclical. Such a process decreases data loss and streamlines later modeling efforts. Second, extended trends, shaped by factors such as economic development and population dynamics, often exhibit serial correlation. ARIMA's autoregressive and moving-average design handles this feature effectively. Third, seasonal movements, mainly driven by climate factors, trigger large swings. Per capita income also tends to introduce heteroscedasticity into economic series, an attribute evident in seasonal components as well. RNNs are highly suitable thanks to their proficiency in processing sequential data and detecting intricate nonlinear relationships. Lastly, the suggested hybrid model provides outstanding forecasting outcomes. Experimental simulations indicate that it surpasses typical time-series techniques, individual neural networks, and further hybrid systems grounded in neural networks.

This research proposes a hybrid prediction framework grounded in detailed insights into monthly electricity demand features. The chief benefit is low reliance on extensive socio-economic or meteorological data, which can be difficult to obtain. In contrast to multivariate models that require reliable external factor projections, this technique effectively bypasses that restriction. The breakdown-and-recombination structure supports improved recognition of key patterns within each element during modeling, delivering better precision than the straightforward use of AI-driven or econometric strategies. In addition, the proposed model provides guidance on production scheduling, network coordination, and end-user consumption plans. Its wide relevance extends to identifying shifts in economic direction and benefiting actors in electricity and carbon markets. In one case, clearing out seasonal effects lets ARIMA forecasts reveal core economic trends, whereas RNN results provide further guidance for electricity and carbon market players.

# Literature Review

## Forecasting models within a multivariate framework

Prior research on monthly electricity demand prediction has primarily focused on developing multivariate models. For example, Chabouni *et al*. [5] employed a causality-driven multiple regression analysis to examine the relationships among electricity demand, air temperature, and other major factors in Algeria. Liu *et al*. [6] studied the influence of temperature shifts on household electricity consumption. Zheng *et al*. [7] constructed an electricity usage prediction framework that draws on diverse socio-economic and climate-related indicators. These efforts focus on anticipating demand variations driven by alterations in socio-economic, demographic, and weather factors. Their key benefit is the ability to measure associations between demand and its drivers, yielding clear, economically significant findings.

Thanks to developments in artificial intelligence, models powered by neural networks have exhibited excellent forecasting capabilities in areas like resources [8, 9], environment [10], and energy [11, 12]. In the field of electricity demand prediction, several studies have employed neural networks using a multivariate approach. Based on climate records,

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Huang *et al*. [13] developed a hybrid system that combines particle swarm optimization with support vector regression. Meanwhile, Ghimire *et al*. [14] introduced a multi-head self-attention transformer system that integrates local climate variables. Pallonetto *et al.* [15] examined the predictive quality of long short-term memory (LSTM) and support vector machine (SVM) systems. Obringer *et al.* [16] presented a multivariate, multisector framework for examining climate sensitivity in the context of joint electricity and natural gas use. Liu *et al.* [17] applied artificial neural networks (ANNs), support vector regression (SVR), and gradient boosting decision trees (GBDTs) to assess how climatic and socio-economic developments affect long-term monthly electricity demand in Hong Kong. Ghimire *et al*. [18] built an interpretable, deeply combined neural network system for electricity demand prediction. Miraki *et al.* [19] proposed a denoising diffusion method for probabilistic prediction of multivariate time series.

Unlike multiple regression, AI-powered models have reduced transparency. In addition, the reliability of multi-variable models frequently hinges on accurate estimations of the input factors. For example, GDP acts as an important driver of electricity demand; thus, adding it to the model ties overall prediction reliability to solid GDP forecasts.

## Forecasting models within a univariate framework

Earlier studies have also pursued model development in a single-variable setting, leveraging historical electricity demand records to forecast future trends using widely used techniques such as Holt-Winters [20, 21], ARIMA [22, 23], and Prophet [24]. With advances in forecasting tools, scholars now acknowledge that an individual model may fall short of capturing all monthly time-series characteristics, prompting greater emphasis on combined approaches. For instance, de Oliveira and Cyrino Oliveira [25] presented a Bagging-driven hybrid system that merges ARIMA and exponential smoothing. Tang *et al*. [26] developed an enhanced seasonal index procedure for predicting grey power usage. Bakare *et al*. [27] recommended a hybrid system combining gene expression and adaptive neuro-fuzzy inference systems to improve forecasts of industrial electricity demand. Wang *et al*. [28] used ensemble empirical mode decomposition combined with particle swarm optimization for SVR, markedly reducing errors in medium-term predictions. Du *et al*. [29] conducted concurrent optimization of point and interval load predictions by fusing time-series decomposition and deep learning. Dong *et al*. [30] offered a hybrid system that pairs the chaotic cuckoo search algorithm with SVR.

Single-variable models offer strong predictive reliability, ease of use, and modest data requirements. This makes them particularly practical in situations where socio-economic, demographic, or meteorological information is insufficient. In actual settings, such data is typically available only at quarterly or annual intervals, which poses obstacles to monthly-level predictions.

## Forecasting models based on decomposition-integration structure

One prevalent tactic in hybrid prediction is to split the raw time series into separate segments, fit prediction models to each segment, and then recombine them for the final forecast [31, 32]. Popular decomposition strategies cover moving averages, polynomial regression, spline functions, empirical mode decomposition (EMD), seasonal and trend decomposition using LOESS (STL), and the HP Filter.

González-Romera *et al*. [33] used moving-average procedures to split electricity demand into trend and fluctuation components, with neural networks predicting the trend and Fourier series handling the fluctuations. Zhu *et al*. [34] proposed a hybrid system that combines seasonal ARIMA (SARIMA) with particle swarm optimization, polishing the raw series using a first-order moving average. Gonzalez-Romera *et al*. [35] used moving averages and cubic splines to derive features from monthly electricity demand. Jaramillo-Morán *et al.* [36] advocated splitting the series into trend and fluctuation parts, then subdividing the fluctuations into six frequency-driven subsequences before predicting each one with neural networks.

Xiong *et al*. [37] built a hybrid system that unites EMD with SVM. Wang *et al*. [28] integrated EMD, sample entropy, particle swarm optimization, and SVR. Shao *et a*l. [38] proposed a prediction system combining semi-parametric approaches with EMD. Gao *et al*. [39] recommended a technique involving improved variation mode decomposition

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(VMD) and refined extreme learning machines using the sparrow search algorithm. Zhang *et al.* [40] recommended a hybrid load prediction system grounded in VMD. Niu *et al*. [41] presented a structure that joins STL and VMD for sequence breakdown, then applies SVR prediction tuned by the grey wolf algorithm. Park *et al*. [42] and Li *et al*. [43] adopted STL to decompose the raw series within their prediction systems. Zhang and Hong [44] used complete ensemble empirical mode decomposition with adaptive noise to formulate a hybrid system.

In addition to the methods listed above, the HP filter has also been applied in hybrid prediction systems. As examples, Yuan *et al*. [45] employed it to separate electricity consumption sequences, and Cancelo *et al*. [46] applied it to extract the trend from Spain's monthly electricity demand. In a similar vein, Bunnoon *et al*. [47] designed a hybrid system combining an HP filter with a two-layer neural network. Herui *et al.* [48] merged the HP filter with ARIMA inside their prediction system. Further research has drawn on singular value decomposition [49, 50] and the wavelet transform [51, 52] to handle time-series breakdown.

The body of work demonstrates that hybrid systems based on sequence decomposition can substantially improve forecasting reliability. Still, Brigato *et al.* [53] noted that no universal model exists for every case, underscoring the importance of the overall model-building approach. Picking the right decomposition strategy matters greatly because each option carries its own traits. For example, the moving average is simple and useful for isolating trends and seasonality, but its effectiveness depends on the chosen window length. STL works iteratively to isolate trend, seasonal, and leftover parts.

Similarly, EMD and wavelet transforms decompose the electricity demand into multiple subseries. Yet these options can create an excess of components, increasing the complexity of building the hybrid system. On top of that, the chosen forecasting tool must align with the specific traits of each component; failing to do so can prevent even cutting-edge techniques from achieving better accuracy.

Building a monthly electricity demand hybrid model in a multivariate setting requires extensive socio-economic, demographic, and meteorological data. Prediction reliability in such cases depends on accurate outlooks for those variables. What is more, the combination of long-term trends and seasonal shifts in monthly electricity demand adds further difficulty to model building. Long-term trends typically result from gradual changes, such as economic expansion and population movements. Seasonal patterns, shaped by weather, tend to be tougher to capture accurately. This study advances a single-variable hybrid prediction model that follows a decomposition-integration approach. The HP filter decomposes electricity demand into a long-term trend and a seasonal component to inform model selection. Given that long-term trends arise mainly from socio-economic drivers and exhibit pronounced temporal dependence, ARIMA proves effective at modeling them through its autoregressive and moving-average framework.

On the other hand, the seasonal component exhibits more pronounced swings and distinct nonlinearity, making it well-suited to neural network modeling. Accordingly, ARIMA and RNNs are used to predict the trend and seasonal parts, respectively. Validation of the suggested approach is based on a case study using Guangzhou's total electricity consumption.

# Materials and Methods

## HP filter

The HP filter is a technique for decomposing time series to extract long-term trends and cyclical components from monthly electricity demand records. Its mathematical expression appears as shown here:

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

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where corresponds to the long-term trend obtained, while denotes the separated seasonal portion. This filter achieves separation by minimizing the loss function Loss(t) in **Eq. 2**. The outcomes depend on the smoothing parameter λ, which is typically set to 14,400 for monthly datasets.

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

Compared to EMD or STL, the HP filter limits the breakdown of electricity demand to trend and seasonal components. Such a division helps reduce data loss while simplifying the later stages of modeling.

## Autoregressive integrated moving average model

ARIMA is a traditional technique for analyzing time series and is represented as ARIMA(p, d, q). Here, p reflects the quantity of autoregressive elements, d indicates the extent of differencing required to reach stationarity, and q represents the number of moving average elements that account for earlier prediction inaccuracies. The ARIMA formulation is given by: where Δ identifies the differencing operator, yt refers to the raw time series, φi and θj serve as the coefficients linked to autoregressive and moving average segments, and εt forms the error component. When dealing with series that include seasonal features, SARIMA becomes the better choice.

Applications of ARIMA in electricity demand prediction remain common. While certain reports suggest that pure ARIMA can sometimes deliver weaker results than competing techniques [54, 55], its integration into combined systems often improves overall precision. Examples include Royal *et al*. [56], who combined ARIMA with the generalized additive model (GAM), and Büyükşahin and Ertekin [57], who paired ARIMA with neural networks in hybrid models. Nie *et al*. [58] introduced an approach linking SVMs to ARIMA, whereas Wu *et al*. [59] developed a hybrid construction combining fractional ARIMA with a refined cuckoo search algorithm. Given that the trend portion isolated by the HP filter has seasonality removed and that ARIMA captures sequential relationships well, the present work applies ARIMA to project the extended trend. Selection of ideal p, d, and q values relies on the Akaike information criterion (AIC).

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

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## Recurrent neural networks

Traditional neural networks include an input layer, multiple or single hidden layers, and an output layer featuring complete connections across layers but none within individual layers. Since time series exhibit sequential relationships, fully

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connected architectures such as backpropagation (BP) often fail to suit these applications. RNNs differ in that they build in sequential relationships via feedback loops, which improves their handling of time series work. **Figure 1** outlines the basic operation of RNNs: the left panel shows an individual neuron, while the right panel reveals its expanded version. Within **Figure 1**, Xt marks the input, Ot stands as the output, and ht indicates the hidden state (memory) at moment t, which follows this definition:

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

Where f(•) acts as the activation function, most often picked as sigmoid or tanh, and U along with V represent the weight matrices. In this setup, the hidden state keeps sequential details moving forward through time steps.

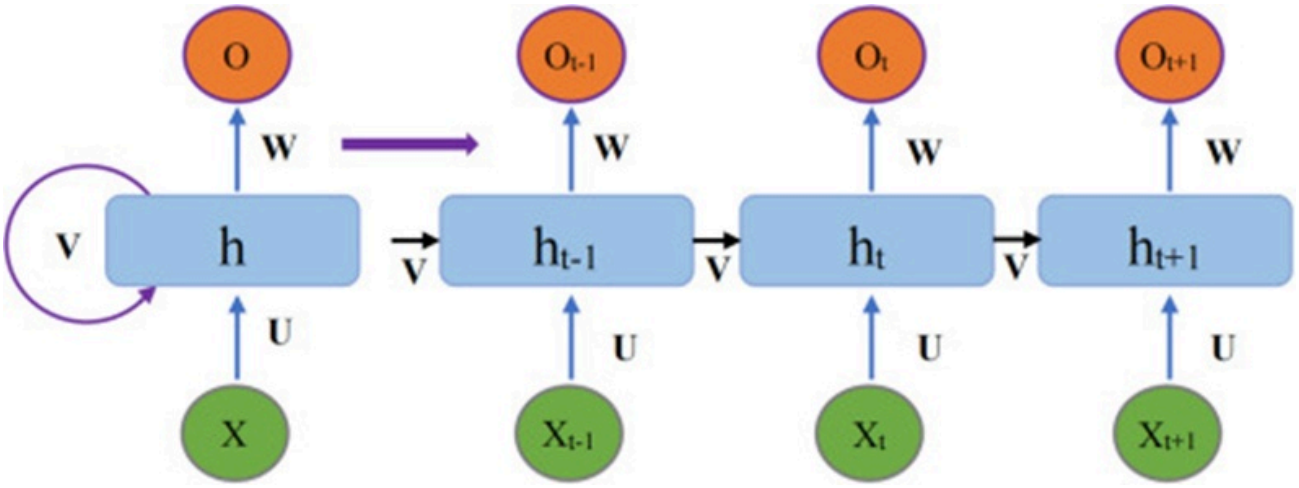


**Figure 1.** Diagram of recurrent neural networks (RNNs).

Each layer at moment t connects strongly to data from the prior moment t–1. The neuron output at moment t, identified as Ot, receives this definition:

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

Here g(•) indicates the activation function, with W serving as the output weight matrix. Generally, U, V, and W remain constant at each time step. RNNs are capable of preserving earlier information, which positions them well for time-series prediction tasks.

Pavlatos *et al*. [60] examined how well RNNs and gated recurrent units (GRUs) performed across different datasets and found that RNNs produced higher accuracy. Similarly, Çunkaş and Altun [61] observed RNNs outperforming BPs. RNNs are also commonly used in the creation of hybrid prediction systems. For instance, Ajitha *et al.* [62] recommended a hybrid system joining RNNs and LSTM to predict residential electricity usage. Yan *et al*. [63] designed a prediction technique based on a hierarchical RNN architecture that splits time series into trend, seasonal, and residual components, allowing RNNs to handle each component before merging them into final estimates. Hussein and Awad [64] introduced a hybrid method that combines RNNs and genetic algorithms for load prediction. For these reasons, the current research applies RNNs to model the isolated seasonal components obtained via HP filtering.

This research uses the Keras platform to build its two-layer RNN. Each layer contains Simple RNN units with 24 neurons, followed by a fully connected output layer (Dense) containing a single neuron for regression-based estimation. Optimization of the system is performed using the Adam algorithm with a learning rate of 0.001. The mean squared error

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(MSE) is used to measure prediction errors. The training process uses mini-batch gradient descent with a batch size of 5 over 35 epochs. Findings verify that the network successfully identifies sequential patterns present in the seasonal portion.

## Assessment of predictive accuracy

Final electricity demand estimates are obtained by combining the separate projections for the trend and seasonal components. **Figure 2** illustrates the overall process of the hybrid prediction system.

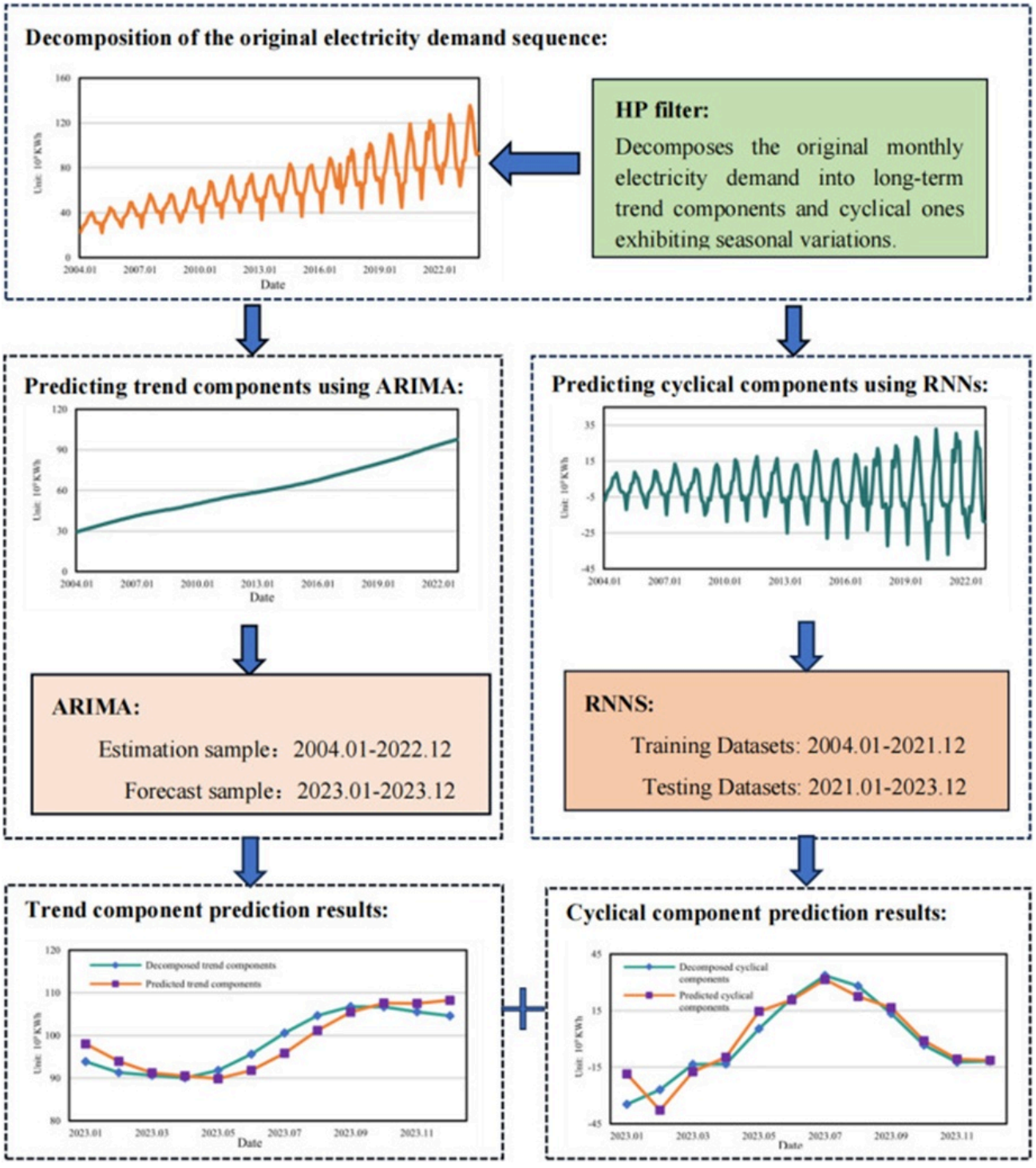


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**Figure 2.** Framework diagram of the proposed forecasting model by combining Hodrick-Prescott filter, recurrent neural networks, and autoregressive integrated moving average.

Evaluation of model prediction quality commonly involves indicators including mean absolute percentage error (MAPE), root mean square error (RMSE), mean absolute error (MAE), and R-squared (R2) [39]. However, selected analyses propose Willmott's index (WI) and Legates and McCabe's index (LMI) as stronger alternatives to R2 for assessing model alignment [9, 14]. The present research applies the assessment standards set out in **Eqs. 6–10** to confirm how the suggested hybrid prediction system performs.

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

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

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

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

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

Where $\hat{y}_i$ and $y_i$ represent the predicted and the actual observed values, respectively, $\bar{y}_i$ denotes the mean of the actual observed values, and n signifies the number of data points predicted.

# Results and Discussion

## Dataset

Electricity consumption data recorded monthly in Guangzhou, China, between January 2004 and December 2023, obtained from the Guangzhou Municipal Bureau of Statistics (https://tjj.gz.gov.cn/), were used to test the predictive performance of the proposed hybrid model. This collection was divided into a training portion running from January 2004 to December 2022 and a testing portion covering January 2023 to December 2023.

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**Figure 3** presents electricity consumption patterns in Guangzhou, highlighting a long-term increase alongside seasonal cycles. Consumption levels normally hit their lowest point in February and their highest in July. The presence of both extended growth trends and recurring variations makes this dataset particularly well-suited for HP filter analysis.

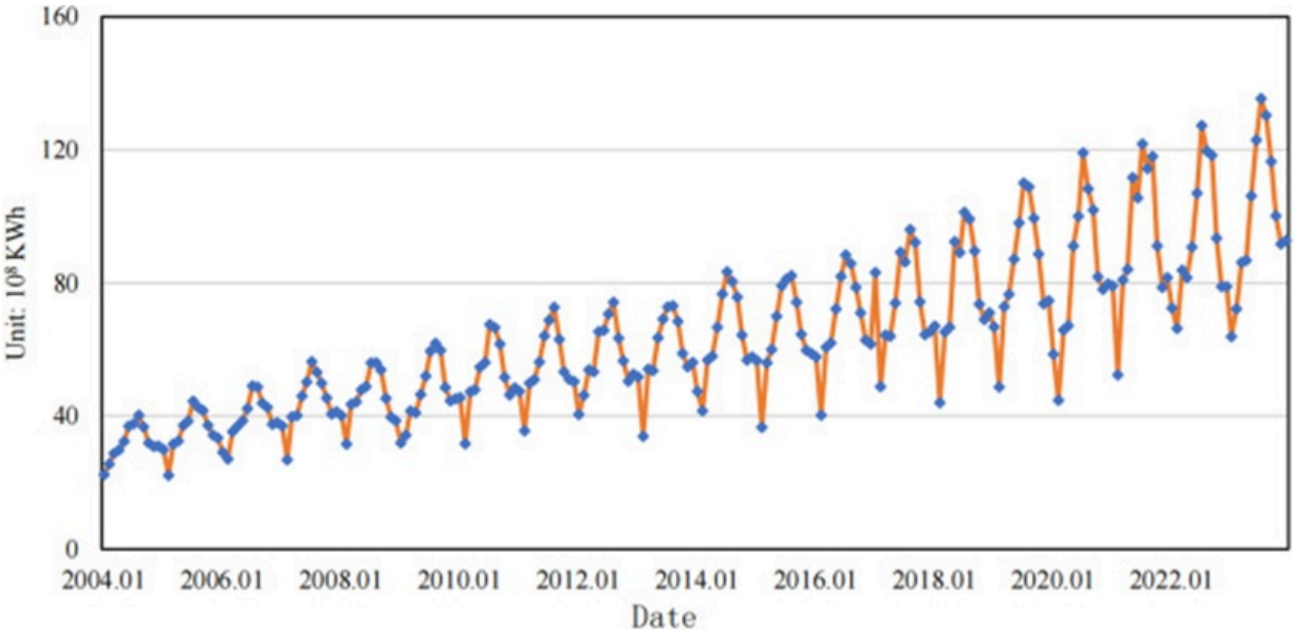


**Figure 3.** Total electricity consumption in Guangzhou, China, from January 2004 to December 2023.

## Results of the HP filter

Implementation of the HP filter on the raw electricity consumption series distinctly separates the extended trend from the seasonal movements **(Figure 4)**. The resulting trend element shows a smoother, more consistent rising path. In contrast, the detached seasonal element reveals clear repeating cycles unaffected by any long-term drift. This breakdown enables forecasting models to more accurately capture the specific behaviors within each segment, thereby improving overall predictive performance.

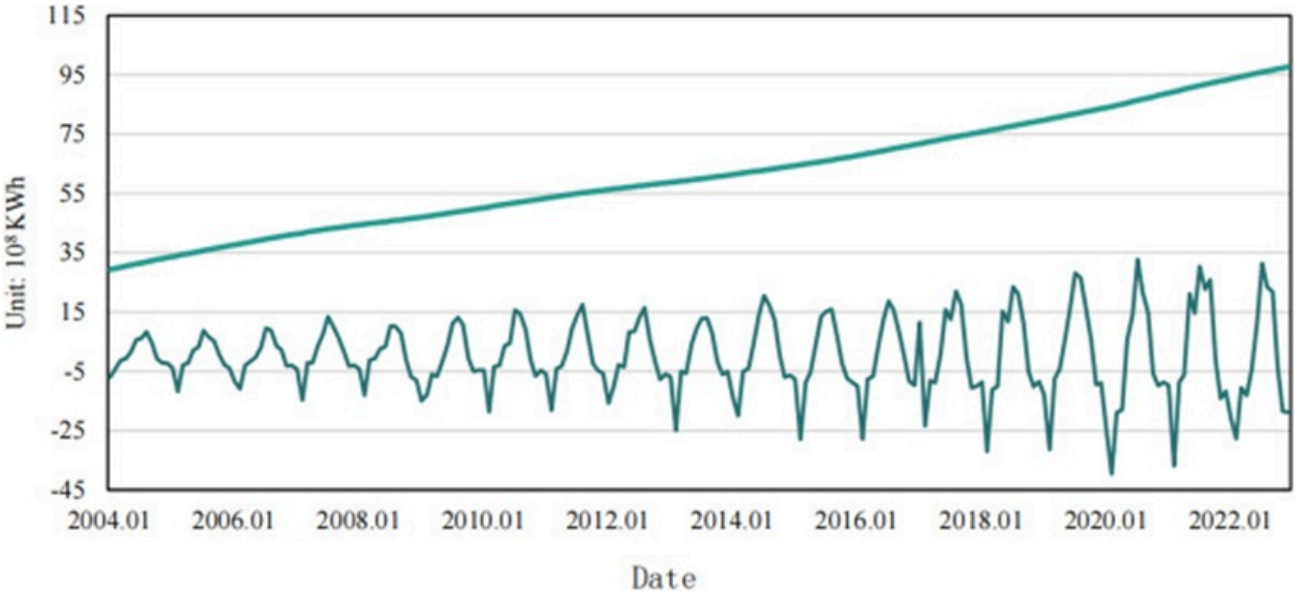


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**Figure 4**. The trend and cyclical components of Guangzhou's total electricity consumption from January 2004 to December 2023, decomposed using the HP filter.

## Trend component prediction results

An ARIMA model was constructed using information from January 2004 to December 2022, with parameter selection guided by the Akaike Information Criterion (AIC). Application of a logarithmic transformation and second-order differencing stabilized the trend, leading to the identification of the ARIMA(4, 2, 3) model as optimal. Rolling one-step-ahead forecasts covering January to December 2023 **(Figure 5)** demonstrate the model's strong capacity to track the separate trend component.

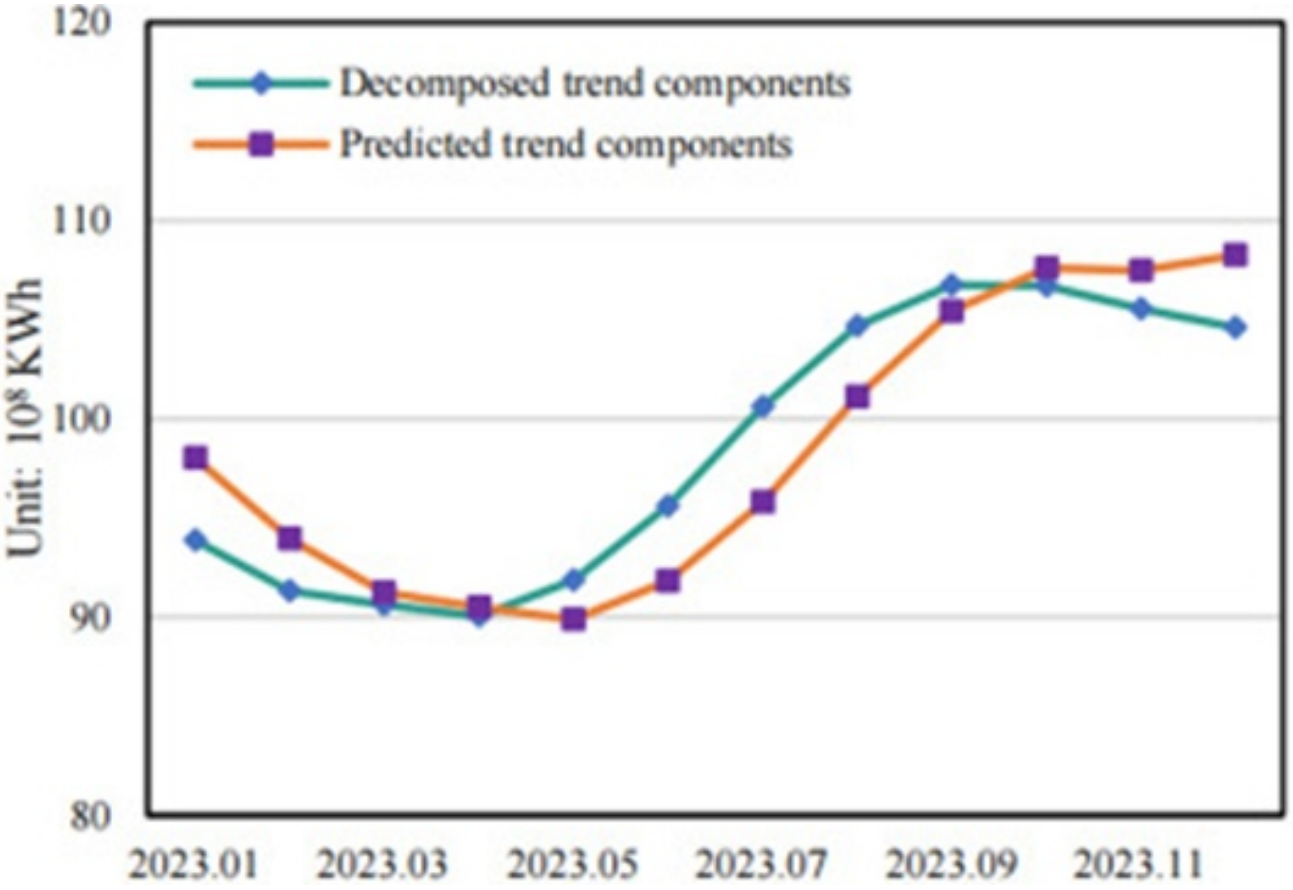


**Figure 5.** Predicted trend component for Guangzhou's total electricity consumption from January 2023 to December 2023.

## Periodic component prediction results

The detached seasonal elements reveal obvious periodic swings that correspond to the original demand patterns, usually bottoming out in February and peaking in August or September. These swings tend to grow in scale over time, indicating clear heteroscedasticity in the series.

RNNs were applied to model the seasonal components, with data from January 2004 to December 2021 for training and data from January 2020 to December 2023 for testing. A 24-month sliding window was utilized to predict the value for the 25th month from the earlier 24 months. The simulations in **Figure 6** indicate that the RNN curve closely tracks the changes observed in the isolated seasonal element.

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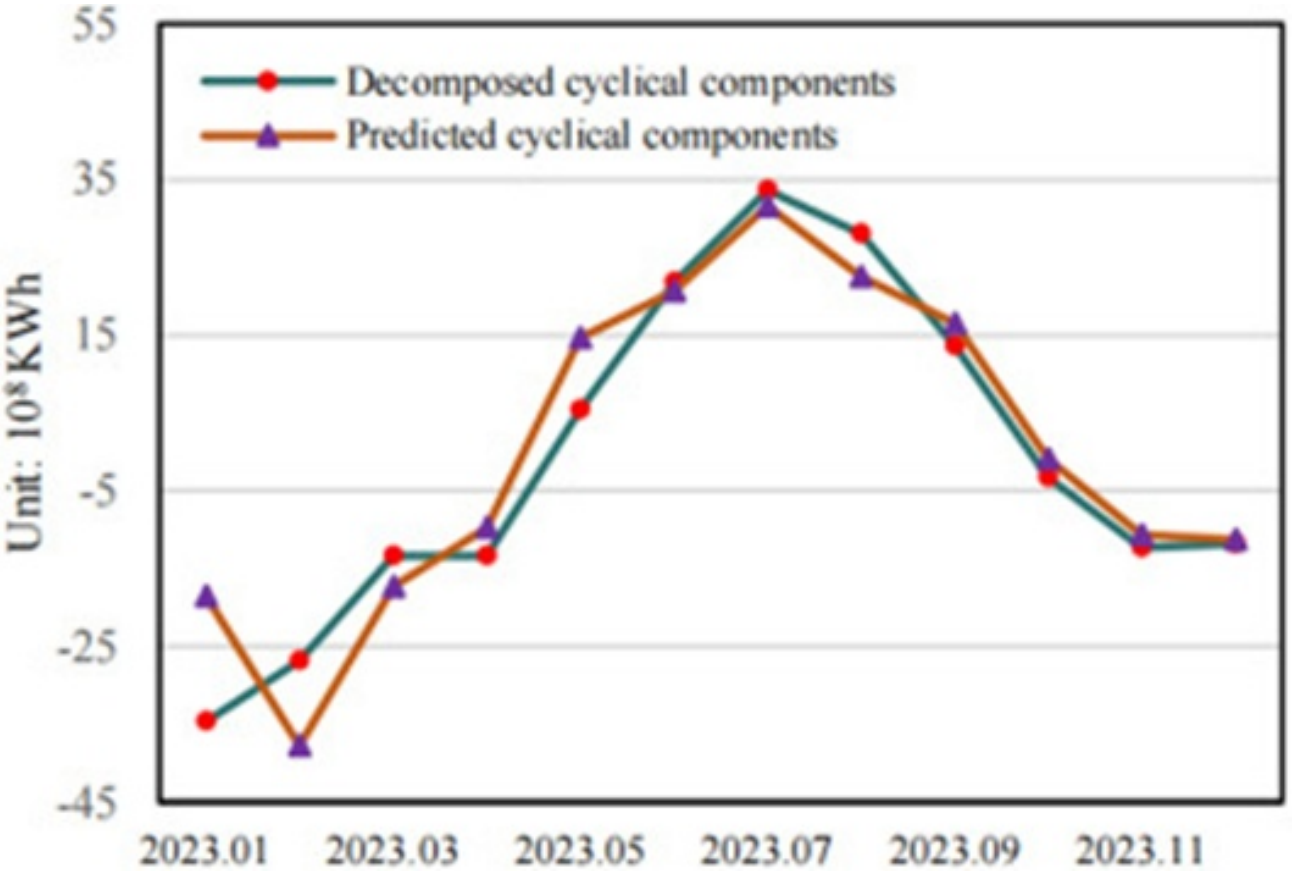


**Figure 6.** Predicted cyclical component for Guangzhou's total electricity consumption from January 2023 to December 2023.

## Comparison of predictive accuracy

Integration of forecasted trends and seasonal elements yields the complete electricity demand projection. **Figure 7** shows close correspondence between the actual and projected values, confirming the precision and usefulness of the proposed hybrid forecasting technique.

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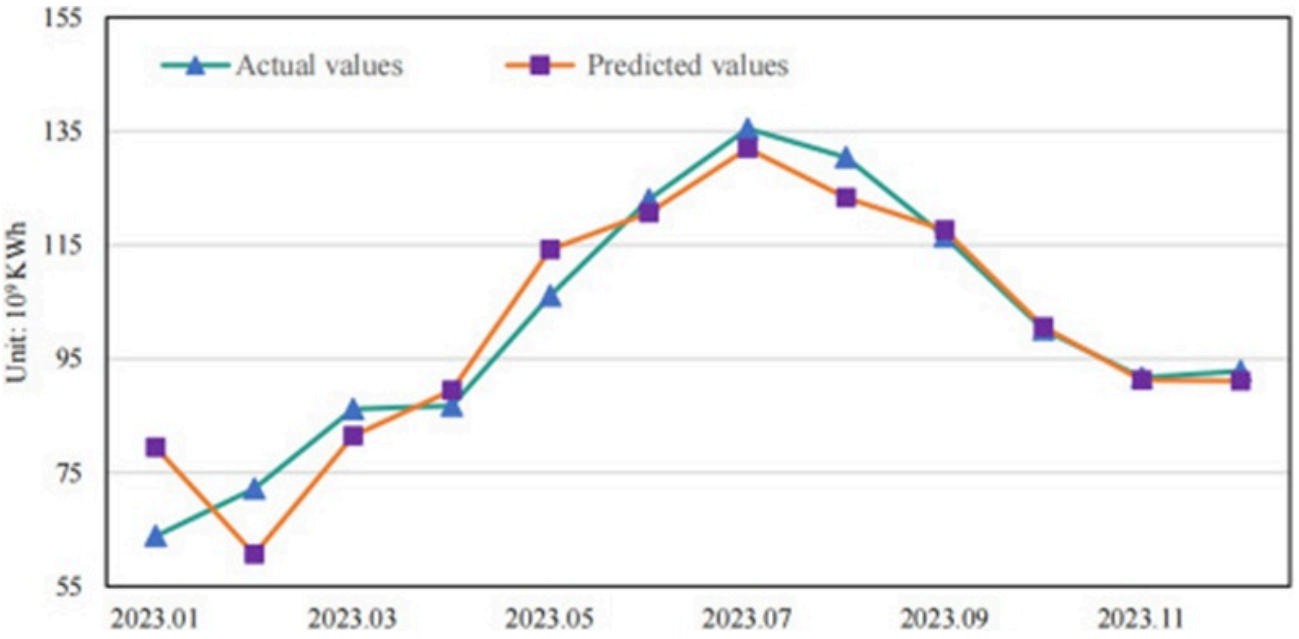


**Figure 7.** The final total electricity consumption forecast for Guangzhou, China, from January to December 2023, derived by reconstructing the prediction results of the trend and periodic components.

## Comparison with classical time series forecasting methods

To evaluate how the proposed hybrid model improves forecast quality, its outputs were compared with common univariate time series methods, including additive Holt-Winters (ADDHW), multiplicative Holt-Winters (MULHW), error-trend-seasonal (ETS), and SARIMA. The new technique is labeled HP_RNN_ARIMA for reference purposes.

**Figure 8** displays forecast comparisons across January to December 2023 for the different models. Notably, all models exhibit larger errors in January and February. This occurs largely because of shifting holiday influences, above all the Chinese Spring Festival, which falls within this timeframe each year. The festival triggers major changes in electricity usage across industrial, commercial, and household sectors, generating sudden variations that models struggle to anticipate.

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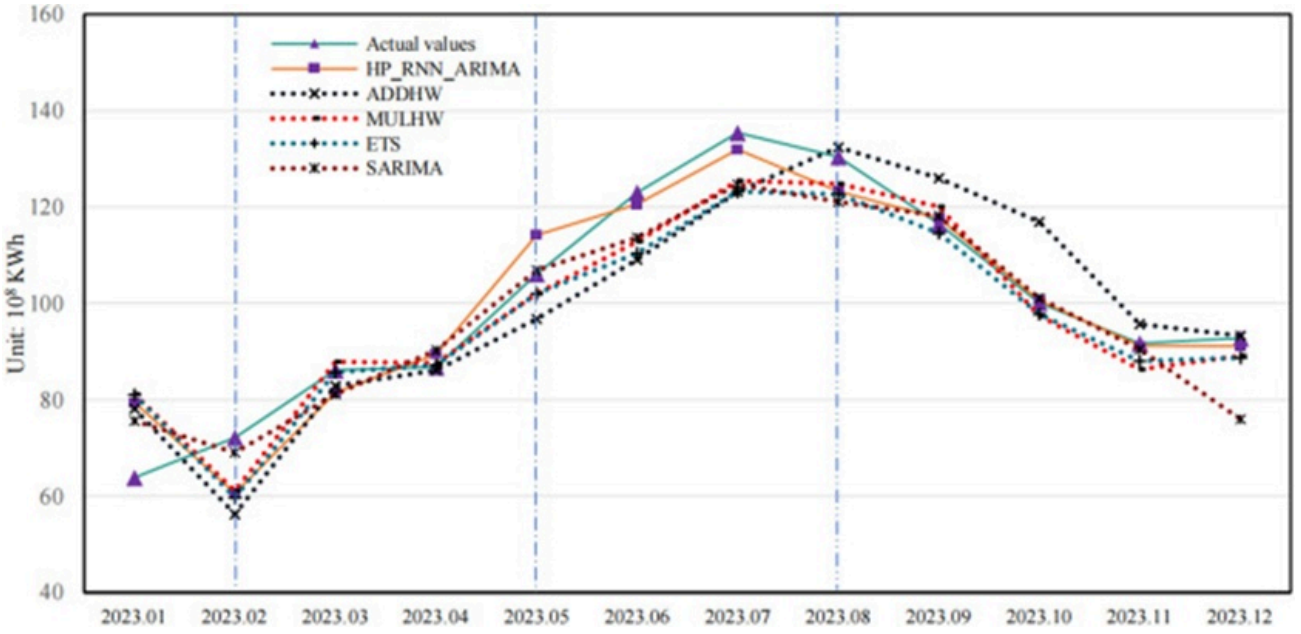


**Figure 8.** A comparison of the hybrid prediction model HP_RNN_ARIMA proposed in this study with traditional time series models, such as ADDHW, MULHW, ETS, and SARIMA, for predicting electricity demand from January to December 2023 in Guangzhou, China.

A further span of clear forecast differences arises from May to August, matching the summer months. Electricity usage during this interval is strongly influenced by weather factors, particularly temperature variations, which significantly shape consumption behavior and pose prediction challenges. The proposed hybrid model HP_RNN_ARIMA performs considerably better than standard techniques in this interval. In March and April, and in September through December, nearly every model except ADDHW delivers solid results, with the suggested model achieving the best overall accuracy.

Table 1 lists outcomes from three accuracy metrics along with two goodness-of-fit metrics for all models. The proposed HP_RNN_ARIMA consistently yields the lowest errors across the accuracy measures, outperforming standard time-series techniques. Calculated accuracy gains show that HP_RNN_ARIMA cuts MAPE by approximately 9.70 % to 35.66 %, RMSE by 14.18 % to 35.06 %, and MAE by 20.01 % to 41.92 %. Regarding goodness-of-fit, WI and LMI show the highest scores, indicating stronger model alignment. Compared with traditional models, WI advances by 0.0125-0.0349, and LMI by 0.0923-0.2206.

**Table 1.** The forecasting performance of the proposed hybrid prediction model HP_RNN_ARIMA vs. ADDHW, MULHW, ETS, and SARIMA as measured by MAPE, RMSE, MAE, WI, and LMI.

| Empty Cell | LMI | | WI | | MAE ($10^8$ KWh) | | RMSE ($10^8$ KWh) | | MAPE ( %) | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Increased | Results | Increased | Results | Improved | Results | Improved | Results | Improved | I |
| **ADDHW** | 0.2206 | 0.5316 | 0.0349 | 0.9389 | 41.92 % | 8.54 | 35.06 % | 10.38 | 35.66 % | |
| **MULHW** | 0.1000 | 0.6522 | 0.0125 | 0.9613 | 21.77 % | 6.34 | 14.18 % | 7.85 | 16.84 % | |
| **ETS** | 0.1150 | 0.6372 | 0.0216 | 0.9522 | 25.00 % | 6.61 | 21.26 % | 8.56 | 18.84 % | |
| **ARIMA** | 0.0923 | 0.6599 | 0.0141 | 0.9597 | 20.01 % | 6.20 | 15.71 % | 7.99 | 9.70 % | |
| **HP_RNN_ARIMA** | | 0.7522 | | 0.9738 | | 4.96 | | 6.74 | | |

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## Comparison with the singular neural networks

The prediction errors of the proposed technique were next evaluated against those of individual neural network models, namely BP, RNNs, and LSTM. Consistency was maintained by using the same neuron quantities, time steps, and training/test divisions as in HP_RNN_ARIMA.

**Figure 9** presents a side-by-side comparison of HP_RNN_ARIMA with the standalone neural network models. Results indicate that individual networks, particularly BP, often fall short of the actual values. Except for January and February, HP_RNN_ARIMA produces lower overall errors and performs especially well during peak usage periods.

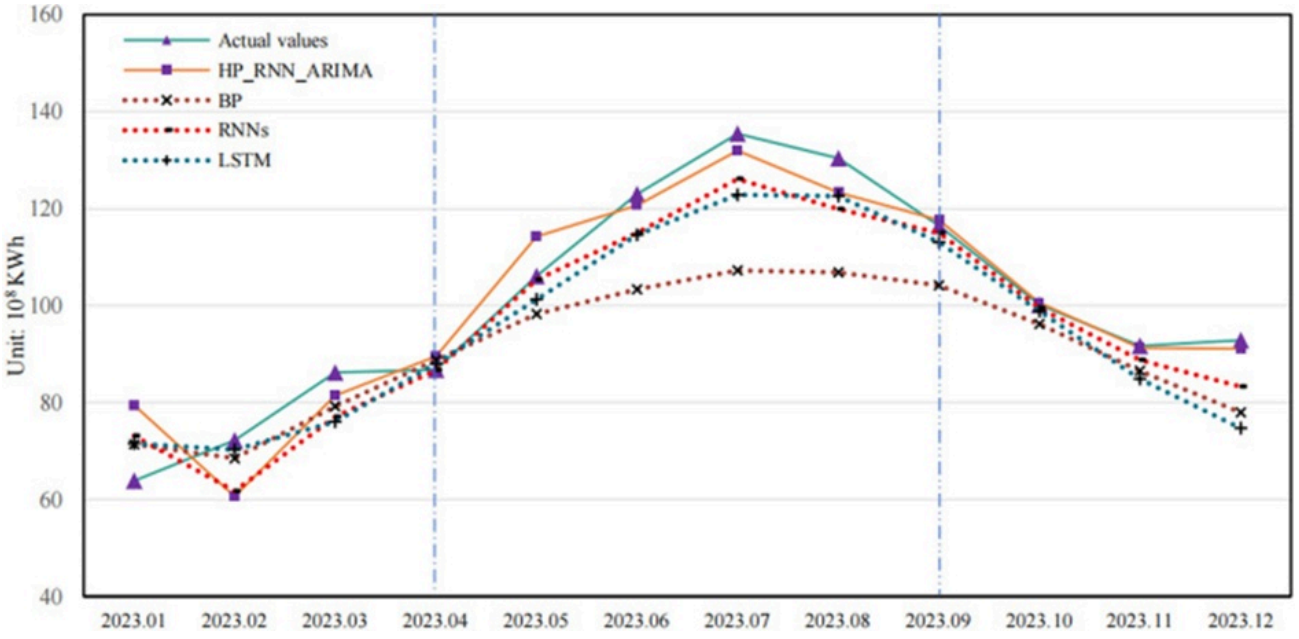


**Figure 9.** A comparison of the proposed hybrid prediction model HP_RNN_ARIMA with singular neural network prediction models, such as BP, RNNs, and LSTM, for predicting electricity demand from January to December 2023 in Guangzhou, China.

**Table 2** details the forecasting outputs for the original electricity demand series produced by the standalone neural networks. The evidence confirms that HP_RNN_ARIMA outperforms all single-network options, achieving the lowest MAPE, RMSE, and MAE. Accuracy computations reveal that HP_RNN_ARIMA trims MAPE errors by roughly 9.05% to 44.02%, RMSE errors by 20.88% to 51.74%, and MAE errors by 29.53% to 56.23%.

**Table 2.** The forecasting performance of the proposed hybrid prediction model HP_RNN_ARIMA vs. BP, RNNs, and LSTM as measured by MAPE, RMSE, MAE, WI, and LMI.

| Empty Cell | LMI | | WI | | MAE ($10^8$ KWh) | | RMSE ($10^8$ KWh) | | MAPE ( %) | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Increased | Results | Increased | Results | Improved | Results | Improved | Results | Improved | I |
| **BP** | 0.3737 | 0.3785 | 0.1253 | 0.8485 | 56.23 % | 11.33 | 51.74 % | 13.96 | 44.02 % | |
| **RNNs** | 0.0831 | 0.6691 | 0.0055 | 0.9683 | 30.16 % | 7.10 | 23.54 % | 8.81 | 9.05 % | |
| **LSTM** | 0.1382 | 0.6140 | 0.0177 | 0.9561 | 29.53 % | 7.04 | 20.88 % | 8.52 | 17.94 % | |

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| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **HP_RNN_ARIMA** | | 0.7522 | | 0.9738 | | 4.96 | | 6.74 | |

Moreover, HP_RNN_ARIMA provides superior WI and LMI scores compared with all other models. Relative to the baseline models BP, RNNs, and LSTM, it elevates WI by 0.1253, 0.0055, and 0.0177 while lifting LMI by 0.3737, 0.0831, and 0.1382, respectively.

**Tables 2 and 3** demonstrate that classical time-series models can outperform neural network methods under certain conditions. In one case, MULHW achieves a MAPE of 7.06%, surpassing LSTM (7.16%) and BP (10.49%). These observations align with previous studies, which note that no single model dominates across all forecasting situations [53].

**Table 3.** The forecasting performance of the proposed hybrid prediction model HP_RNN_ARIMA vs. BP_DEC, RNN_DEC, and LSTM_DEC as measured by MAPE, RMSE, MAE, WI, and LMI.

| Empty Cell | **LMI** | | **WI** | | **MAE ($10^8$ KWh)** | | **RMSE ($10^8$ KWh)** | | **MAPE ( %)** | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **Increased** | **Results** | **Increased** | **Results** | **Improved** | **Results** | **Improved** | **Results** | **Improved** | I |
| **BP_DEC** | 0.2457 | 0.5065 | 0.0465 | 0.9273 | 44.87 % | 8.99 | 36.67 % | 10.64 | 33.39 % | |
| **RNN_DEC** | 0.0369 | 0.7153 | 0.0023 | 0.9715 | 4.43 % | 5.19 | 4.27 % | 7.04 | 3.60 % | |
| **LSTM_DEC** | 0.0456 | 0.7066 | 0.0066 | 0.9672 | 7.27 % | 5.35 | 6.47 % | 7.21 | 8.96 % | |
| **HP_RNN_ARIMA** | | 0.7522 | | 0.9738 | | 4.96 | | 6.74 | | |

## Comparison with other hybrid models

As a final step, various HP-filter-based hybrid models were built using different strategies and benchmarked against HP_RNN_ARIMA. Every alternative first breaks down the series using the HP filter before predicting the trend and seasonal components with a single neural network type (BP, RNNs, or LSTMs), identified as BP_DEC, RNN_DEC, and LSTM_DEC, respectively.

**Figure 10** shows the forecasting performance of HP_RNN_ARIMA relative to the alternative hybrid versions. BP_DEC yields the least favorable outcomes, often falling short of actual consumption figures. LSTM_DEC notably exceeds actual figures from January to July, coinciding with periods of rising demand. RNN_DEC shows behavior close to HP_RNN_ARIMA yet generally under-predicts, yielding modestly lower accuracy.

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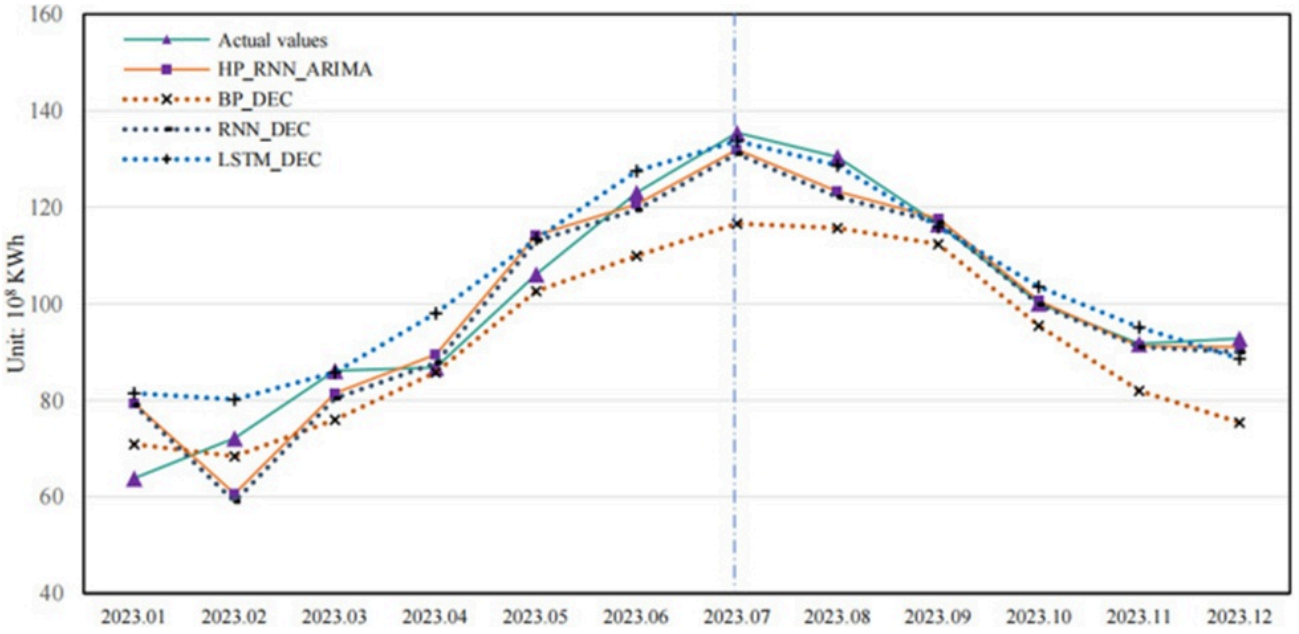


**Figure 10.** A comparison of the proposed hybrid prediction model HP_RNN_ARIMA with other hybrid models, such as BP_DEC, RNN_DEC, and LSTM_DEC, for predicting electricity demand from January to December 2023 in Guangzhou, China.

**Table 3** presents the prediction results for the hybrid models and shows that HP_RNN_ARIMA achieves the smallest errors across the board. Compared with BP_DEC, RNN_DEC, and LSTM_DEC, it reduces MAPE by 3.6% to 33.39%, RMSE by 4.27% to 36.67%, and MAE by 4.43% to 44.87%. It additionally raises WI by 0.0465, 0.0023, and 0.0066, and LMI by 0.2457, 0.0369, and 0.0456, respectively. Results also indicate that ARIMA is better at modeling long-term trends, while RNNs are better at modeling cyclical movements than BP or LSTM.

Analysis of **Tables 2 and 3** shows that HP filter decomposition of the raw electricity demand data, applied before neural network modeling, improves forecast quality. To illustrate, the basic BP network yields MAPE, RMSE, and MAE values of 10.49%, 13.96%, and 11.33%, respectively. Meanwhile, the HP-enhanced BP_DEC version achieves 8.82%, 10.64%, and 8.99%, reducing errors by 15.92%, 23.80%, and 20.60%, respectively.

Likewise, RNN_DEC decreases MAPE, RMSE, and MAE by 5.65%, 20.14%, and 26.93% relative to the plain RNN, whereas LSTM_DEC achieves reductions of 9.87%, 15.40%, and 24.00%. Consequently, HP filtering, which divides the series into trend and cyclical segments, enables neural networks to identify distinct variation patterns more precisely. This division limits overlap interference between extended trends and periodic signals, substantially lifting predictive performance.

Assessments of additional forecasting strategies confirm that the proposed model yields the smallest MAPE, RMSE, and MAE, along with the largest WI and LMI scores, solidly establishing its enhanced accuracy and reliability.

In total, the suggested approach diminishes MAPE-related errors by roughly 3.6% to 44.02% **(Figure 11)**, RMSE-related errors by around 4.27% to 51.74% **(Figure 12)**, and MAE-related errors by 4.43% to 56.23% **(Figure 13).** Within **Figures 11-13** : PFEI represents the percentage drop in prediction errors relative to the top-performing HP_RNN_ARIMA model. On goodness-of-fit aspects, WI advances by about 0.0023 to 0.1253 **(Figure 14)**, and LMI grows by around 0.0369 to 0.3737 **(Figure 15)**.

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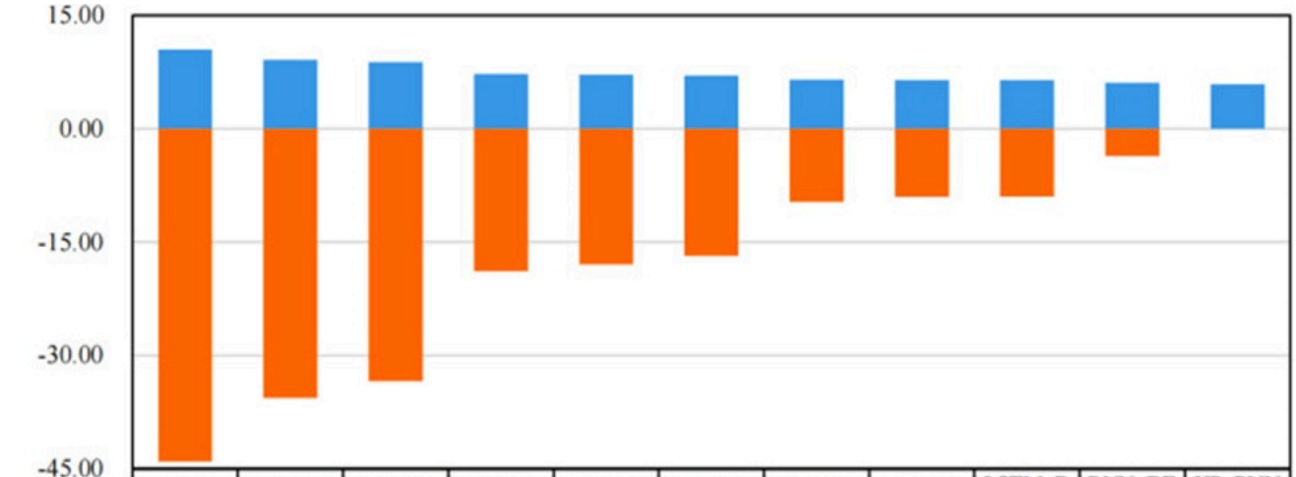
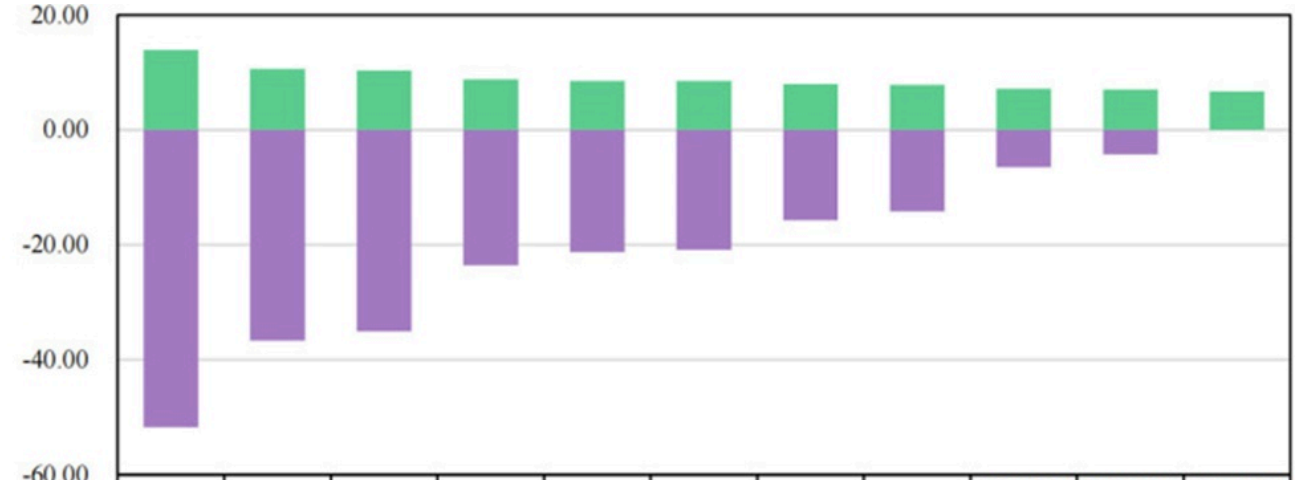



| | BP | ADDHW | BP_DEC | ETS | LSTM | MULHW | SARIMA | RNNs | LSTM_DEC | RNN_DEC | HP_RNN_ARIMA |
|---|---|---|---|---|---|---|---|---|---|---|---|
| PFEI(%) | -44.02 | -35.66 | -33.39 | -18.84 | -17.94 | -16.84 | -9.70 | -9.05 | -8.96 | -3.60 | 0.00 |
| MAPE(%) | 10.49 | 9.13 | 8.82 | 7.24 | 7.16 | 7.06 | 6.50 | 6.46 | 6.45 | 6.09 | 5.87 |

**Figure 11.** The MAPE for various forecasting models, along with the percentage improvement in prediction error compared to HP_RNN_ARIMA. Negative values represent decreased prediction error.




| | BP | BP_DEC | ADDHW | RNNs | ETS | LSTM | SARIMA | MULHW | LSTM_DEC | RNN_DEC | HP_RNN_ARIMA |
|---|---|---|---|---|---|---|---|---|---|---|---|
| PFEI(%) | -51.74 | -36.67 | -35.06 | -23.54 | -21.26 | -20.88 | -15.71 | -14.18 | -6.47 | -4.27 | 0.00 |
| RMSE | 13.96 | 10.64 | 10.38 | 8.81 | 8.56 | 8.52 | 7.99 | 7.85 | 7.21 | 7.04 | 6.74 |

**Figure 12**. The RMSE for various forecasting models, along with the percentage improvement in prediction error compared to HP_RNN_ARIMA. Negative values represent decreased prediction error.

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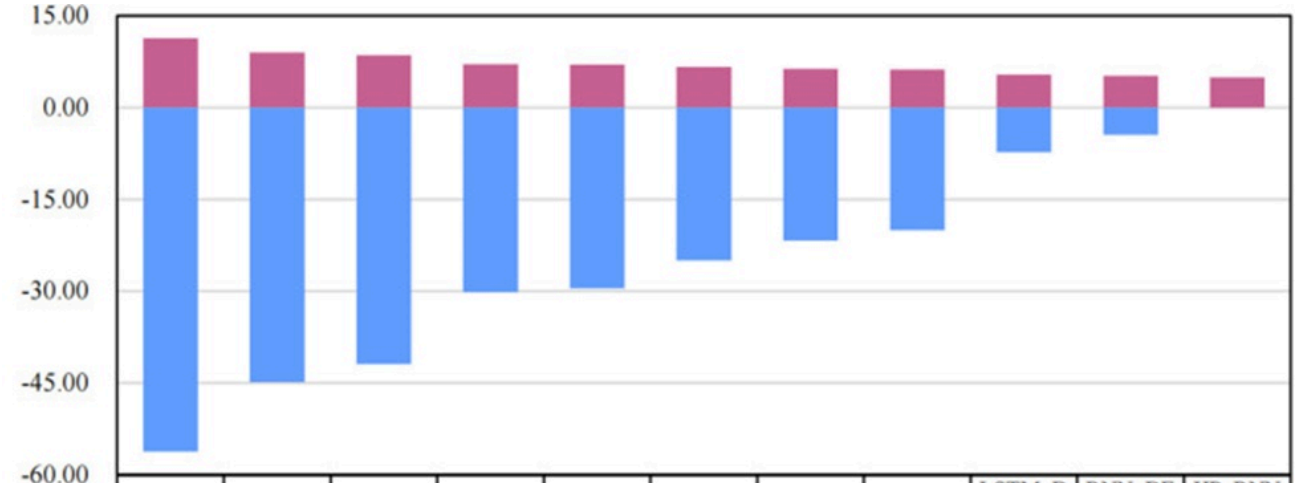
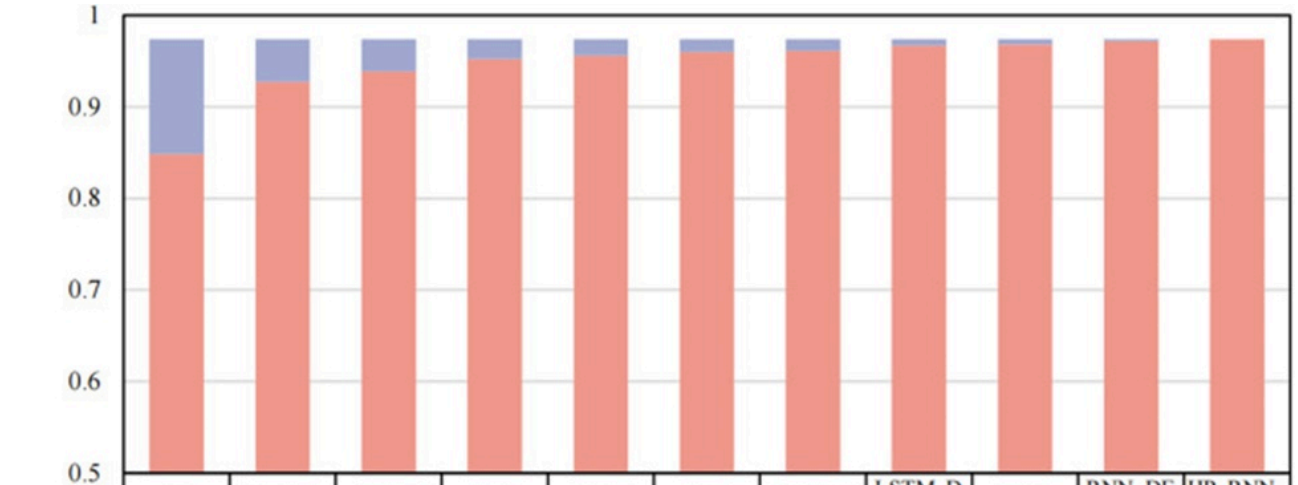



| | BP | BP_DEC | ADDHW | RNNs | LSTM | ETS | MULHW | SARIMA | LSTM_DEC | RNN_DEC | HP_RNN_ARIMA |
|---|---|---|---|---|---|---|---|---|---|---|---|
| PFEI(%) | -56.23 | -44.87 | -41.92 | -30.16 | -29.53 | -25.00 | -21.77 | -20.01 | -7.27 | -4.43 | 0.00 |
| MAE | 11.33 | 8.99 | 8.54 | 7.10 | 7.04 | 6.61 | 6.34 | 6.20 | 5.35 | 5.19 | 4.96 |

**Figure 13.** The MAE for various forecasting models, along with the percentage improvement in prediction error compared to HP_RNN_ARIMA. Negative values represent decreased prediction error.




| | BP | BP_DEC | ADDHW | ETS | LSTM | ARIMA | MULHW | LSTM_DEC | RNNs | RNN_DEC | HP_RNN_ARIMA |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Increased | 0.1253 | 0.0465 | 0.0349 | 0.0216 | 0.0177 | 0.0141 | 0.0125 | 0.0066 | 0.0055 | 0.0023 | 0 |
| WI | 0.8485 | 0.9273 | 0.9389 | 0.9522 | 0.9561 | 0.9597 | 0.9613 | 0.9672 | 0.9683 | 0.9715 | 0.9738 |

**Figure 14.** The goodness-of-fit for various models, as measured by WI, and the potential for improvement compared to the optimal HP_RNN_ARIMA model.

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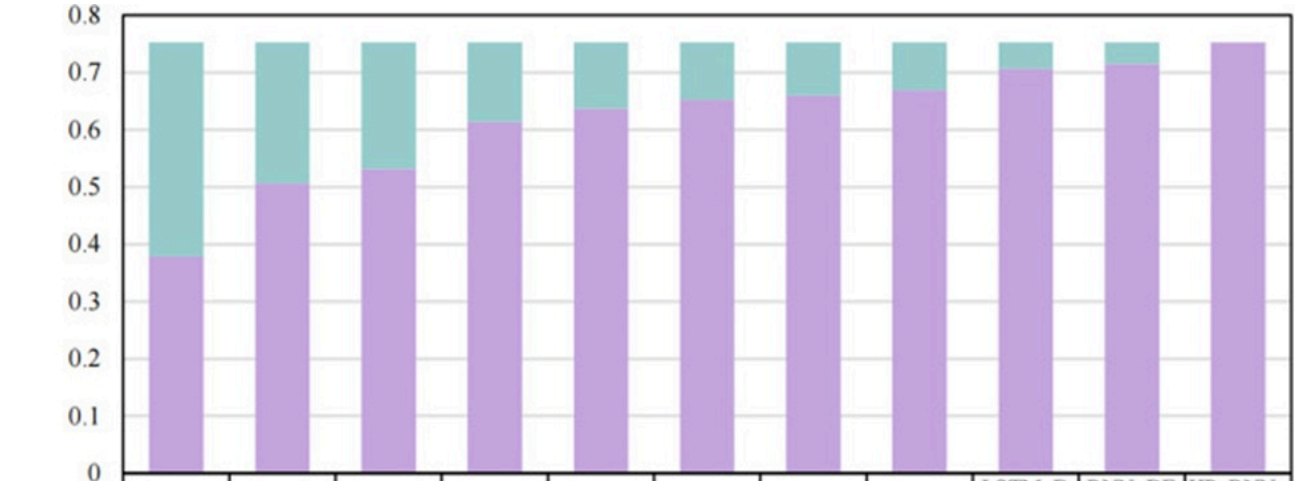


| | BP | BP_DEC | ADDHW | LSTM | ETS | MULHW | ARIMA | RNNs | LSTM_DEC | RNN_DEC | HP_RNN_ARIMA |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Increased | 0.3737 | 0.2457 | 0.2206 | 0.1382 | 0.115 | 0.1 | 0.0923 | 0.0831 | 0.0456 | 0.0369 | |
| LMI | 0.3785 | 0.5065 | 0.5316 | 0.614 | 0.6372 | 0.6522 | 0.6599 | 0.6691 | 0.7066 | 0.7153 | 0.7522 |

**Figure 15.** The goodness-of-fit for various models, as measured by LMI, and the potential for improvement compared to the optimal HP_RNN_ARIMA model.

HP_RNN_ARIMA, RNN_DEC, and LSTM_DEC consistently achieved the highest positions across all error and goodness-of-fit measures (MAPE, RMSE, MAE, WI, and LMI), demonstrating consistent, robust performance. In comparison, the remaining models produced more fluctuating results, implying weaker stability. These observations highlight the benefit of HP filtering when decomposing time series.

# Conclusion

This research presents a univariate time-series forecasting technique that begins with HP filtering to split monthly electricity demand into trend and cyclical components. Dedicated ARIMA and RNN models then produce separate forecasts for each segment before their combination into the overall prediction. The technique is validated using Guangzhou's electricity consumption records spanning January 2004 to December 2023.

Outcomes reveal that the developed hybrid model outperforms conventional approaches, including Holt-Winters, ARIMA, and ETS, as well as standalone neural networks such as BP, RNNs, and LSTM, and their hybrid versions. HP filtering successfully isolates segments with unique fluctuation traits, thereby reducing interference from mixed long-term trends and cyclical movements while improving forecast quality.

One primary strength of this hybrid forecasting model is its deliberate pairing of techniques with the specific variation traits in the separate series. ARIMA performs better at capturing long-term trends in electricity usage, while RNNs excel at recognizing seasonal patterns within the cyclical segments. The integration of established statistical techniques with contemporary AI methods yields substantial advances in prediction accuracy.

The suggested hybrid forecasting model remains uncomplicated, simple to deploy, and operates with modest data requirements, facilitating easy adoption into ongoing operational or marketing platforms of electricity producers, grid managers, and major users. It delivers dependable assistance for functions such as scheduling operations and engaging in electricity markets.

Importantly, the proposed hybrid forecasting model operates within a univariate time-series setup, enabling forecasts independent of supplementary socio-economic information. Its primary shortcoming is its inability to incorporate factors such as economic expansion, population growth, and climate change, which may limit its application in broad energy

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policy formulation. Furthermore, despite significant interest in weather-driven electricity shortages, the existing technique omits a detailed examination of the influence of climate change on electricity demand. Later investigations will expand this base by integrating socio-economic, demographic, and climatic factors to construct multivariate time-series forecasting models.

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# Conflict of interest

None

# Financial support

None

# Ethics statement

None

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