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Adaptive Electricity Price Forecasting via Switching Mother Wavelets and LSTM Networks

Andrei Popa^{1*}, Mihai Georgescu¹, Elena Dobre², Sorin Iancu¹

Abstract

In the context of dynamic pricing, reliable and precise demand-side electricity price forecasting is crucial for effective energy management. We propose a new electricity price forecasting model that delivers consistently accurate predictions. The underlying prediction framework decomposes the time series via a wavelet transform before applying Long Short-Term Memory for forecasting. Earlier research using this framework has consistently applied the same mother wavelet for decomposition, without variation. Nevertheless, this fixed approach struggles to adapt to the daily or seasonal fluctuations inherent in the time series. To address this limitation, we introduce periodic switching of the mother wavelet, effectively enabling flexible modification of the decomposition technique and yielding stable, high-accuracy electricity price forecasting. Experimental evaluation revealed that the model enhanced prediction accuracy by up to 42.8% relative to the version employing a fixed mother wavelet. The findings confirm that this flexible forecasting approach reliably produces highly accurate results.

Keywords Dynamic pricing, Electricity price forecast, Wavelet transform, Long short-term memory neural network

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Introduction

Over recent years, renewable energy sources have seen widespread adoption across numerous countries. These resources are anticipated to support the transition toward a low-carbon society. Although renewable energy is environmentally friendly, its generation cannot be actively regulated. Within power systems, balancing electricity supply with demand remains fundamental. Failure to do so may trigger voltage and frequency instability, leading to significant disruptions to end users' electrical devices. As a result, utility companies routinely predict demand levels and regulate output from individual power plants to maintain equilibrium between supply and demand.

At present, the extensive penetration of solar energy into power grids has intensified the difficulty of achieving this balance. Demand response has therefore emerged as a promising strategy to mitigate these issues [1]. It involves adjusting end-users' consumption behavior. A prominent form of demand response is dynamic pricing [2], which adjusts electricity rates at regular intervals and has been implemented in various regions, including European countries, the United States, and Australia. For instance, during periods of anticipated surplus generation, prices can be reduced to encourage higher consumption. As electricity prices fluctuate continuously under dynamic pricing schemes, the ability to anticipate these variations becomes essential for informed consumer decisions. In particular, accurate electricity price forecasting is vital for prosumers—entities that both consume and generate electricity—whose numbers are rising as solar installations expand. By relying on dependable price predictions, prosumers can optimize their energy usage to

secure bill incentives while contributing to collective energy efficiency without interfering with broader national or regional grid optimization efforts.

Approaches to electricity price forecasting generally fall into three primary groups: statistical, machine learning, and hybrid. Among statistical techniques, Auto-Regressive (AR) models—including Auto-Regressive Integrated Moving Average (ARIMA) and Generalized Auto-Regressive Conditional Heteroscedasticity (GARCH)—have enjoyed broad application. Zhao *et al.* [3] applied an ARIMA model to differenced price time-series data, modeling the price as a weighted combination of historical prices plus random noise. Their work also accounted for variations in consumption behavior on weekdays versus holidays by integrating a dedicated “weekday/holiday” component into the model, thereby boosting short-term forecast precision. Tan *et al.* [4] introduced a hybrid technique that integrates the wavelet transform with ARIMA and GARCH models, validating its performance on Spanish electricity market data and additional datasets. Mohsenian-Rad and Leon-Garcia [5] highlighted a strong correlation between current electricity prices and those observed 1, 2, and 7 days previously. They derived the predicted price as a weighted average of values from these preceding days and adjusted the daily weights to minimize forecasting errors. Nonetheless, statistical methods of this nature make predictions by linearly combining past observations, meaning that extending the historical window requires additional parameters and complicates the modeling of intricate, nonlinear patterns. For this reason, machine learning methods are increasingly favored for their effectiveness in addressing complex and nonlinear relationships.

Machine learning approaches have found applications in numerous research domains. For instance, Wei [6] applied machine learning techniques to forecast stock prices. Durganjali and Pujitha [7] used classification methods, including logistic regression and decision trees, to estimate the resale value of residential properties. Lu *et al.* [8] developed an electricity price forecasting framework centered on an Artificial Neural Network (ANN). Lago *et al.* [9] benchmarked various machine learning strategies, including basic deep neural networks (DNNs) and LSTM, against conventional statistical techniques such as ARIMA. Their analysis revealed that machine learning strategies generally outperformed statistical techniques in terms of prediction accuracy. Xu and Baldick [10] conducted a comparative analysis of simple Recurrent Neural Network (RNN), LSTM, and Gated Recurrent Unit (GRU) against neural networks lacking recursive components. The results indicated that simple RNNs, LSTM, and GRU achieved better performance by leveraging historical data in their predictions. Collectively, these investigations underscore the advantages of RNN variants such as LSTM and GRU for electricity price forecasting. Still, hybrid frameworks that combine machine learning with complementary techniques have become the dominant trend lately, owing to their ability to produce more precise electricity price estimates than standalone machine learning solutions.

Peng *et al.* [11] employed a differential evolution algorithm for optimizing LSTM parameters. Operating under the premise that this would improve the modeling of time-series features, they observed gains in forecast precision when testing on electricity price records from New South Wales, Australia, as well as from markets in Germany, Austria, and other locations. Lago *et al.* [12] demonstrated that combining Lasso Estimated Auto-Regressive (LEAR) with a DNN in a hybrid setup yielded superior results compared to applying LEAR or DNN separately, and statistical validation confirmed meaningful differences in accuracy. Given its strength in managing non-stationary series, the fusion of machine learning algorithms with wavelet transform has attracted considerable research interest, extending well beyond electricity price applications to other fields. Wavelet transform functions decompose a time series into its frequency components. Su *et al.* [13] constructed a prediction system for natural gas usage that combines wavelet transforms, a deep learning-based RNN architecture, and a Genetic Algorithm. Through this decomposition, the wavelet transform reduced the complexity of the prediction process by breaking the raw consumption data into distinct subseries. Su's investigation selected Daubechies 4 to serve as the mother wavelet. Barzegar *et al.* [14] examined the performance of four alternative models for estimating river water salinity at a site in northwestern Iran, including an ANN, an Adaptive Neuro-Fuzzy Inference System (ANFIS), a wavelet-enhanced ANN, and a wavelet-enhanced ANFIS. The mother wavelets tested ranged from Daubechies 1 to 7, Symlet 3 to 5, and Haar, with Daubechies 4 achieving the highest accuracy. The researchers attributed this superiority to the close resemblance between the functional form of Daubechies 4 and the characteristics of the salt concentration time series under study. Liu *et al.* [15] introduced a short-term wind power prediction technique grounded in wavelet transform paired with LSTM, adopting Daubechies 7 as the mother wavelet. In the field of electricity price forecasting, Aggarwal *et*

al. [16] presented a neural network architecture supported by a wavelet transform to anticipate price movements in power markets. Their evaluation covered Daubechies 1-4 as possible mother wavelets, ultimately selecting Daubechies 2. The experiments confirmed that embedding the wavelet transform improved overall forecasting performance. Singh *et al.* [17] incorporated generalized neurons—which require comparatively little training data—into a hybrid architecture alongside a wavelet transform, choosing Daubechies 4 as the mother wavelet once again. This work also assessed several error measurement criteria and confirmed their effectiveness using electricity price data from New South Wales, Australia.

Chang *et al.* [18] developed a combined wavelet transform and LSTM framework and assessed its effectiveness using datasets from New South Wales, Australia, and France. Following the pattern observed in earlier research, the wavelet transform provided an initial breakdown of the time series. The electricity price sequence was separated into multiple lower-variance sub-series. LSTM networks were independently trained to predict each sub-series, and their outputs were combined to form the complete price forecast. This frequency-based decomposition produced data with steadier variance, which, in turn, enabled LSTM to model electricity price movements with greater precision. Findings indicated that the suggested framework markedly improved prediction accuracy relative to Peng's approach [11] and an alternative that pairs ARIMA with an ANN [19]. Notably, Chang's investigation generated future price estimates exclusively from prior price records. In our earlier research, we extended their wavelet-LSTM hybrid [20] by integrating electricity demand data as an additional input to improve accuracy. This adjustment reduced errors by up to 53.7% for one-step-ahead forecasts (predicting the price an hour ahead). Both Chang's original effort and our prior implementation used Daubechies 5 as the mother wavelet.

Mother wavelets come in many forms, each offering unique benefits and limitations for decomposing time series, with performance closely tied to the underlying pattern of the target data, as highlighted by Barzegar *et al.* [14]. Despite actual electricity price sequences exhibiting evolving patterns over time, every previously cited study used a single, unchanging mother wavelet across the full length of the testing window—even when separate trials compared different options. Put differently, although the characteristics of the series shift from one interval to the next, the selected mother wavelet stayed constant within each experiment. Accordingly, the current research aims to design an innovative model that delivers more consistent accuracy by regularly switching the mother wavelet. As far as the authors are aware, this type of forecasting architecture represents a first-time application not only in electricity price contexts but also across time-series prediction in general and other forecasting scenarios. The chief contribution of the present paper is the introduction of an electricity price forecasting technique that is innovative in some respects and refined in others, specifically tailored to accommodate variations in price behavior across days and seasons.

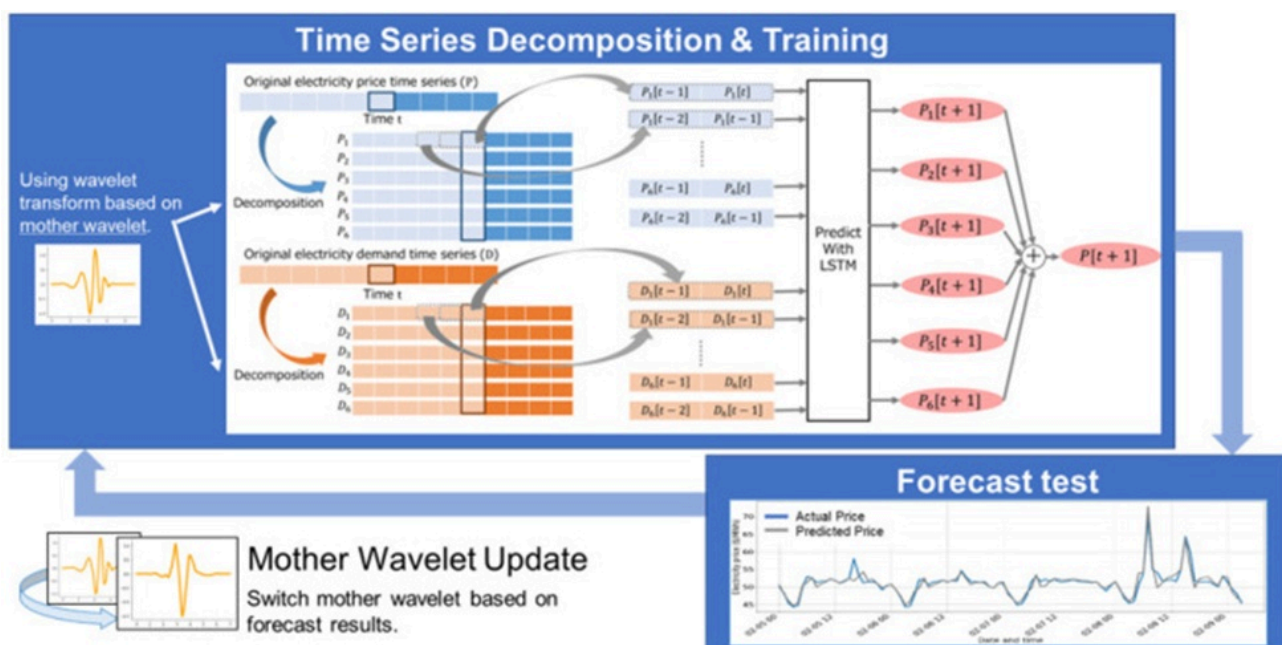


Figure 1. Overview of proposed method; training and forecast test are repeated while switching mother wavelets based on forecast results. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

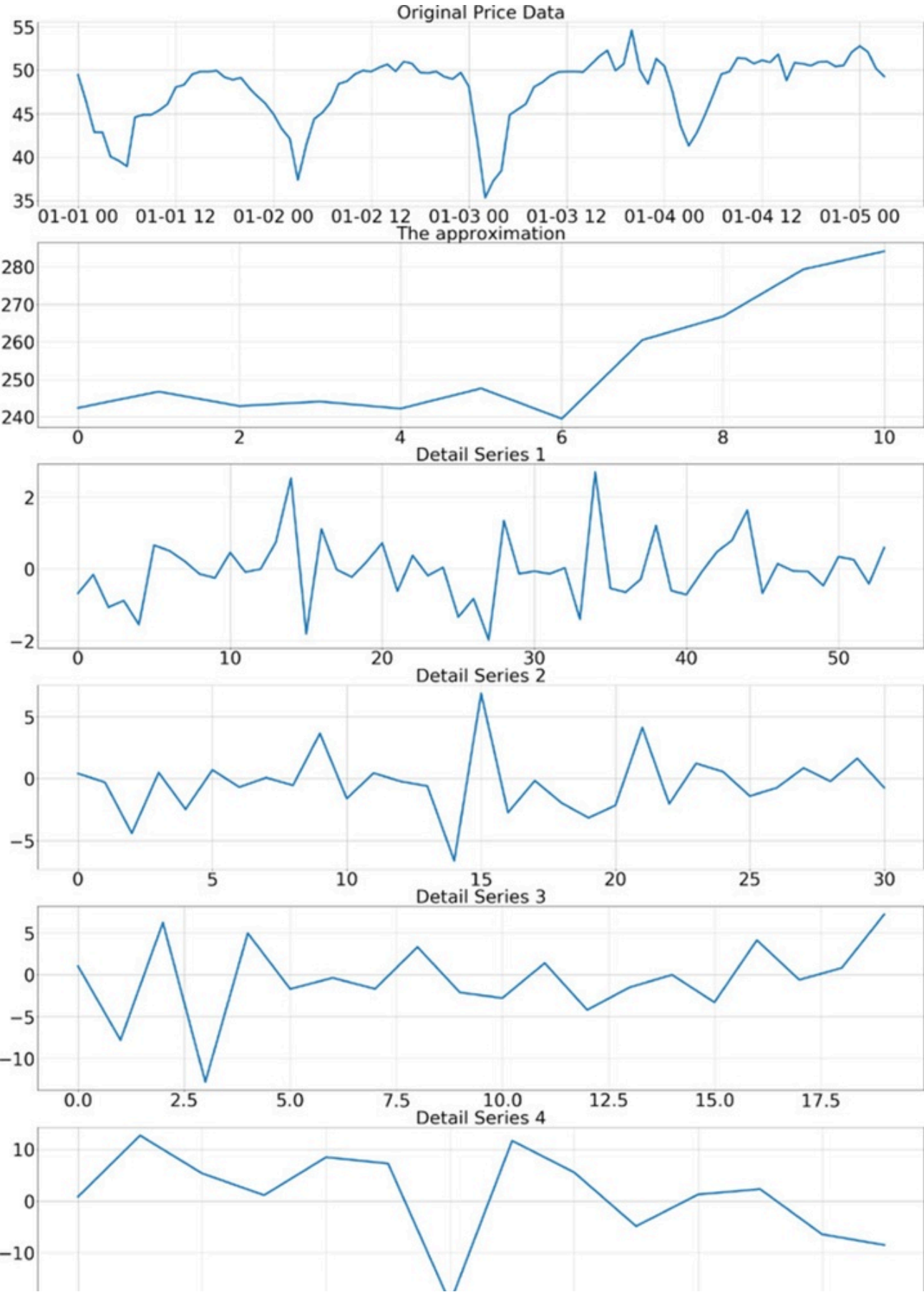
Materials and Methods

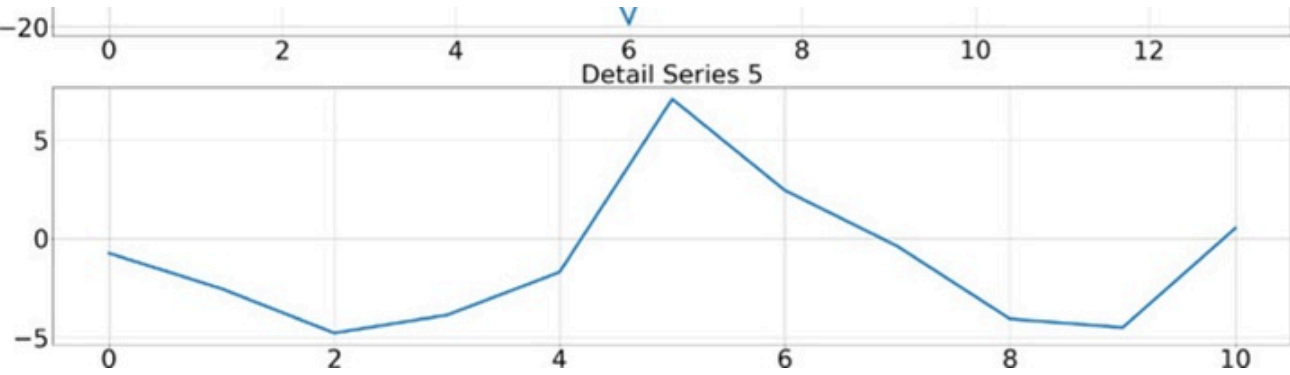
The technique presented in this paper is designed to generate reliable and precise forecasts by regularly alternating the mother wavelet inside the integrated wavelet transform and LSTM architecture. **Figure 1** illustrates the overall structure of the suggested technique. The process starts by decomposing both the electricity price and demand time series into various frequency bands using the wavelet transform. Each resulting sub-series is subsequently trained using LSTM networks to predict upcoming electricity prices. Wavelet transform includes an important setting called the mother wavelet, and the quality of the decomposition varies depending on how well this mother wavelet fits the specific pattern of the time series. To counteract any decline in forecasting performance, the proposed technique periodically replaces the mother wavelet with a more suitable one that better corresponds to the evolving shape of the data. This part of the paper first provides a thorough explanation of the combined wavelet transform and LSTM model with reference to **Figure 1**, and then outlines the procedure for switching between mother wavelets.

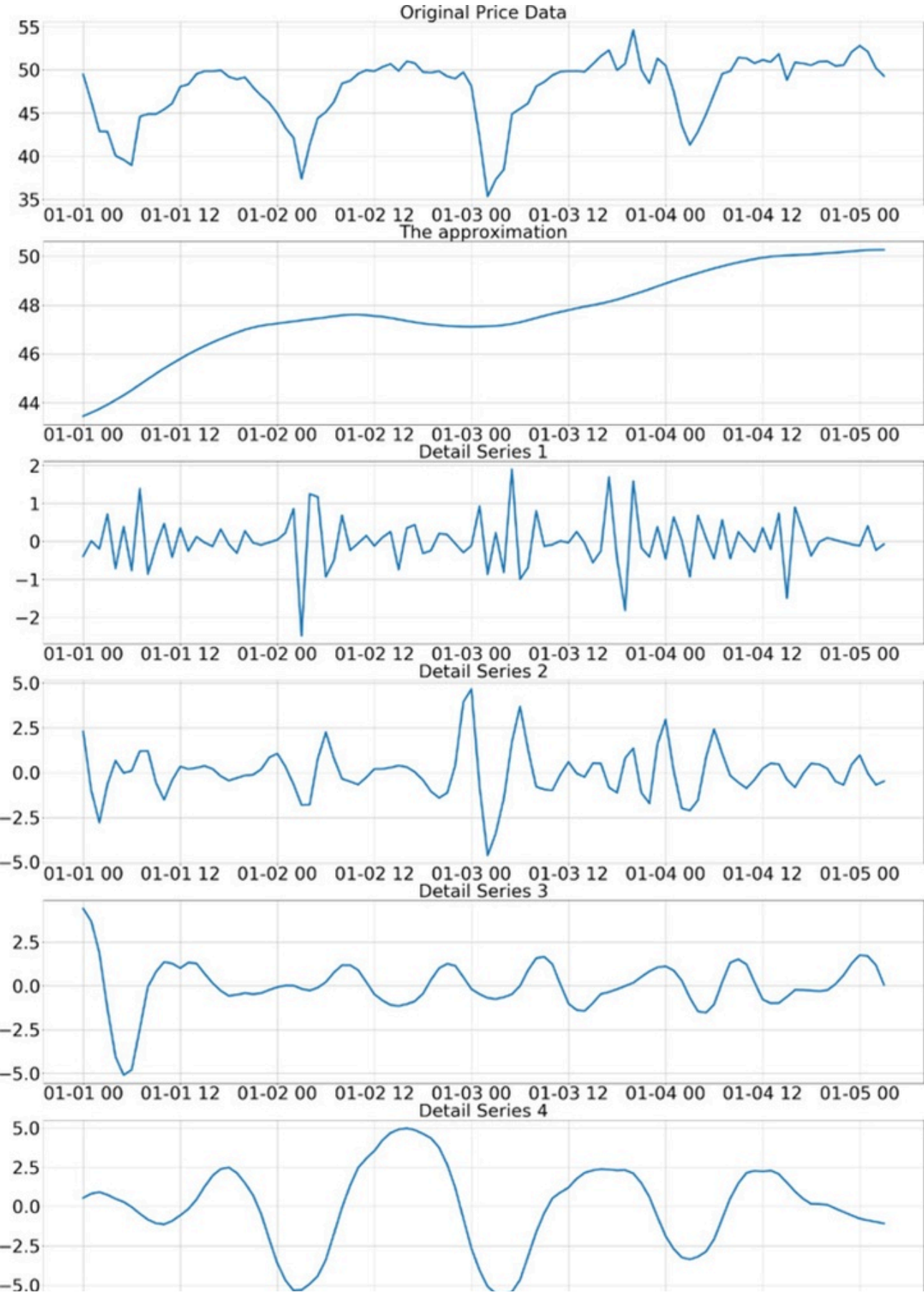
Hybrid model of wavelet transform and LSTM

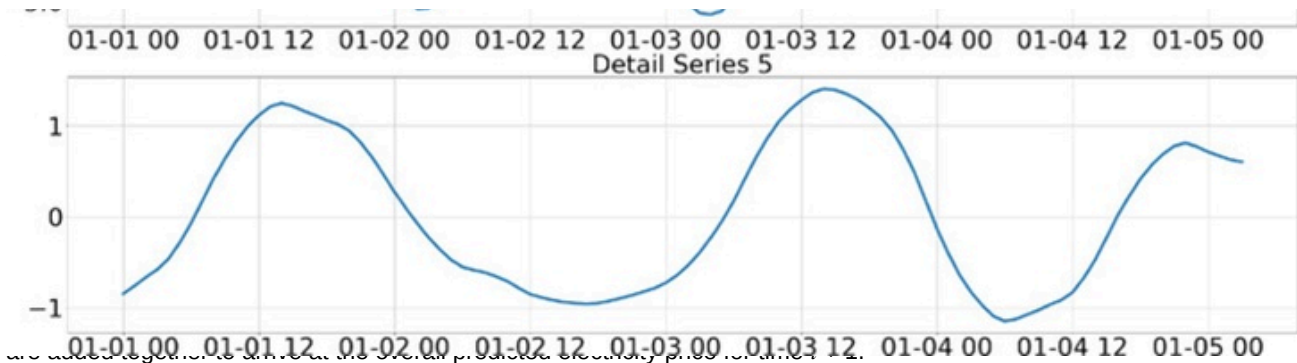
Generating forecasts with the hybrid wavelet transform and LSTM model requires three essential phases: data preparation, breakdown of the time series, and prediction via LSTM. During data preparation, outliers are identified and treated according to the Pauta criterion, while both electricity price and demand values are scaled using Min–max normalization. Subsequently, the wavelet transform is applied to decompose the electricity price and demand series into separate frequency components. The decomposition depth was maintained at level 5, matching the setting from the earlier research [20]. The wavelet-based decomposition process for time series is depicted in **Figures 2 and 3**. Although the electricity price series is used for illustration, the same steps are followed for the electricity demand series. The raw price series is first passed through a wavelet transform, yielding the component series shown in **Figure 2**. The approximation part isolates the low-frequency trend. In contrast, the detail parts capture higher-frequency components, such as sudden variations. Afterward, the inverse wavelet transform reconstructs each component back into the original time domain, as shown in **Figure 3**.

With the time series now separated into components by wavelet transform, LSTM networks are trained individually on every sub-series. The LSTM architecture employed for prediction features an input layer, a central LSTM layer, and an output layer, where the LSTM layer uses the sigmoid activation function. Optimization was performed using Adam [21]. Key hyperparameters—such as the number of LSTM neurons, total training epochs, batch size, and the Adam learning rate—were automatically selected to allow an impartial assessment of the model's effectiveness [9]. Parameter selection relied specifically on the tree-structured Parzen estimator [22], a Bayesian optimization technique. This estimator was preferred because it readily accommodates continuous, discrete, categorical, and conditional variables alike—features that are challenging for traditional Bayesian optimization routines. It also demands comparatively low computational effort [23]. Once the LSTM model processes each component series to produce forecasts for the electricity price components, the full predicted price is computed by summing the outputs from all individual components.









Switching mother wavelet

The wavelet transform used to decompose time series operates on principles similar to those of the Fourier transform. Just as the Fourier transform reconstructs the original signal through scaled and shifted sine and cosine functions, the wavelet transform relies on short, localized wave functions referred to as mother wavelets to achieve the same purpose. Given the wide variety of available mother wavelets, the resulting forecasting error can differ markedly depending on the choice made.

Nine mother wavelets that are frequently adopted in time series prediction tasks, appear in [Figure 4](#). The families Daubechies (db) and Symlet (sym) are identified by their names, with the number that follows representing the vanishing moment. Analogous to the degree of a polynomial, greater vanishing moments result in smoother wavelet shapes. In typical time-frequency analysis using the wavelet transform, selecting the most appropriate mother wavelet is generally advised by evaluating how closely its form matches the pattern of the series being examined [\[24\]](#). As demonstrated in [Figure 5](#), the actual pattern of the electricity price time series fluctuates noticeably across different intervals. For instance, prices in New South Wales, Australia, displayed strong volatility between April and August 2013, in contrast to the more moderate movements observed from September to December.

For this reason, the objective is to maintain high forecasting accuracy by routinely updating the mother wavelet to better align with changing daily and seasonal patterns. The proposed technique decomposes and forecasts using the range of mother wavelets shown in [Figure 4](#), then selects the most suitable one to produce the final output. In the selection mechanism, the mother wavelet that achieved the best performance over the preceding n weeks is chosen for the current forecast. While intra-month variations are less dramatic than the seasonal contrasts highlighted previously, [Figure 5](#) reveals that the series pattern still evolves meaningfully within a month. In contrast, alterations over only a few days tend to be minimal for electricity prices. Accordingly, the switching of mother wavelets was implemented on a weekly schedule. The ideal setting for n will be determined in the subsequent section by assessing the performance of the proposed technique.

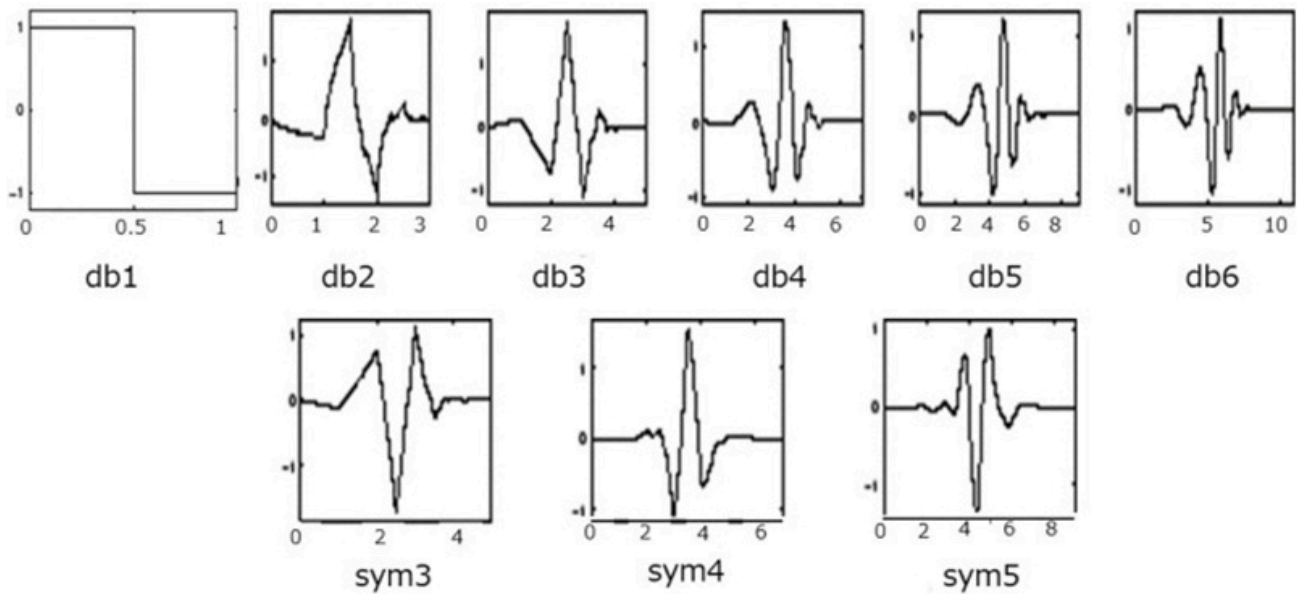


Figure 4. Mother wavelet function often used in time series forecasting [25].

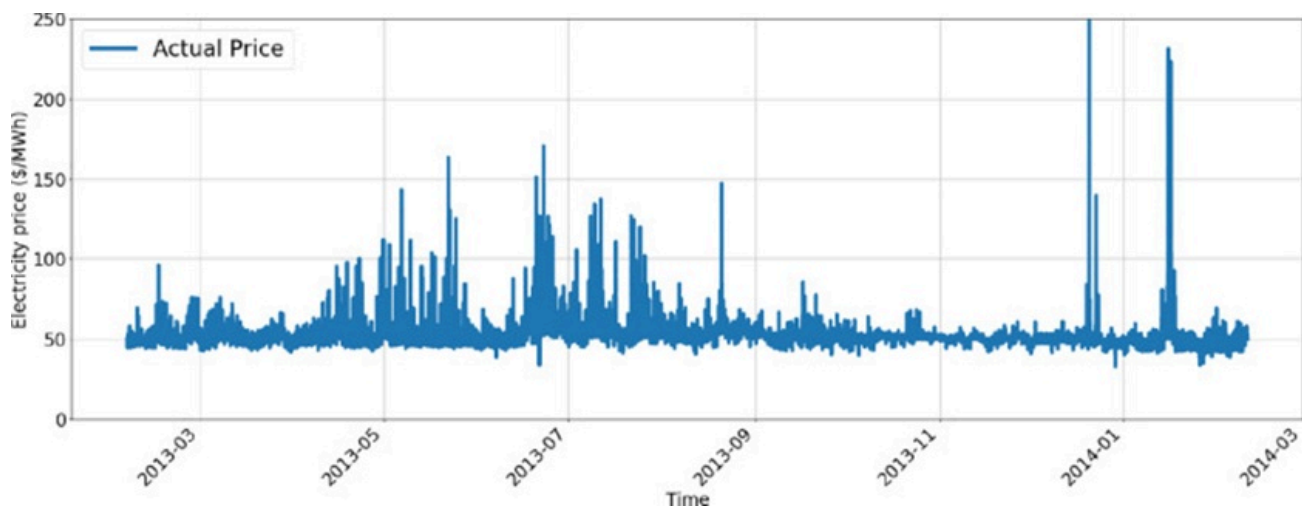


Figure 5. Electricity prices in New South Wales, Australia, in 2013 [26].

Experimental Evaluation

Experimental setup

Testing was performed to assess the adaptable forecasting technique developed in this paper. The testing conditions replicated those applied in our prior investigation [20]. The analysis drew on electricity price and demand records from New South Wales, Australia, covering 2013. These records are provided by the Australian Energy Market Operator (AEMO) [26]. Although the source material recorded values at 30-minute intervals, the study used hourly-resolution data. The forecasting exercise involved one-step-ahead prediction, in which the electricity price for the upcoming hour is estimated at each hourly point. Figure 6 presents the concept of one-step-ahead prediction at time t . In both the upper and lower diagrams, the horizontal axis denotes time, and the vertical axis represents electricity prices; solid lines indicate known historical prices, while dotted lines indicate prices yet to be determined. Although Figure 6 displays only electricity

prices, the same steps are followed when handling electricity demand. At present t , the price expected at $t + 1$ is calculated from price and demand data spanning $t - 2$ to t . One hour afterward, at time $t + 1$, the values from $t - 1$ to $t + 1$ serve as the basis for predicting the price at $t + 2$. This process continues on an hourly basis.

Altogether, the experiment covered 19 distinct mother wavelet setups: nine setups with a constant mother wavelet drawn from Daubechies (db) 1 through 6 and Symlet (sym) 3 through 5, plus ten setups under the proposed technique where the parameter n (the number of weeks reviewed for switching) ranged from 1 to 10.

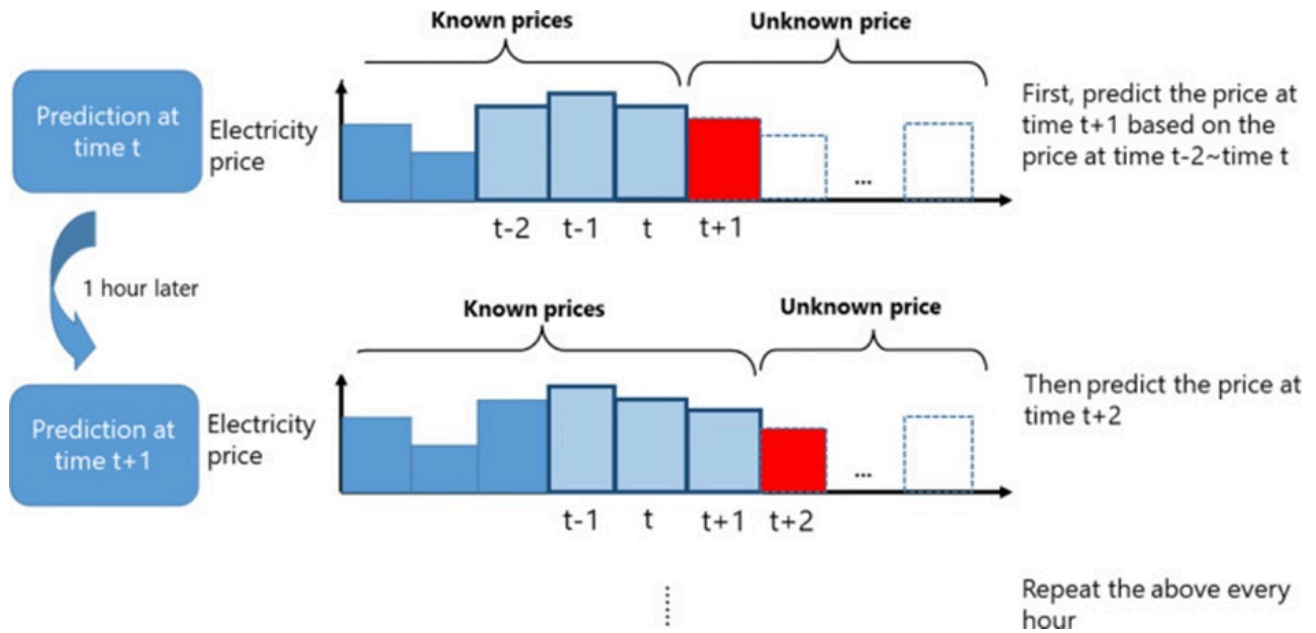


Figure 6. Overview of one-step-ahead prediction.

For the full length of the experiment, forecasts were produced by performing time series decomposition and model training on a weekly cycle, as depicted in **Figure 7**. More precisely, the model was initially trained using price and demand records spanning the four weeks from January 1 to January 28, 2013. Data from January 29 to February 4 were then set aside as validation data to examine how well the model had learned. Predictive performance was subsequently tested on data covering February 5 to February 11. Following this, the entire dataset was shifted forward by 1 week, and the decomposition, training, validation, and testing sequence was repeated. This procedure was repeated over 53 weeks, covering nearly a full year. Model performance was measured using the Mean Absolute Percentage Error (MAPE), defined as follows:

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

Where n represents the number of observations, y_i denotes the actual value, and $\hat{y}_i$ stands for the predicted value.

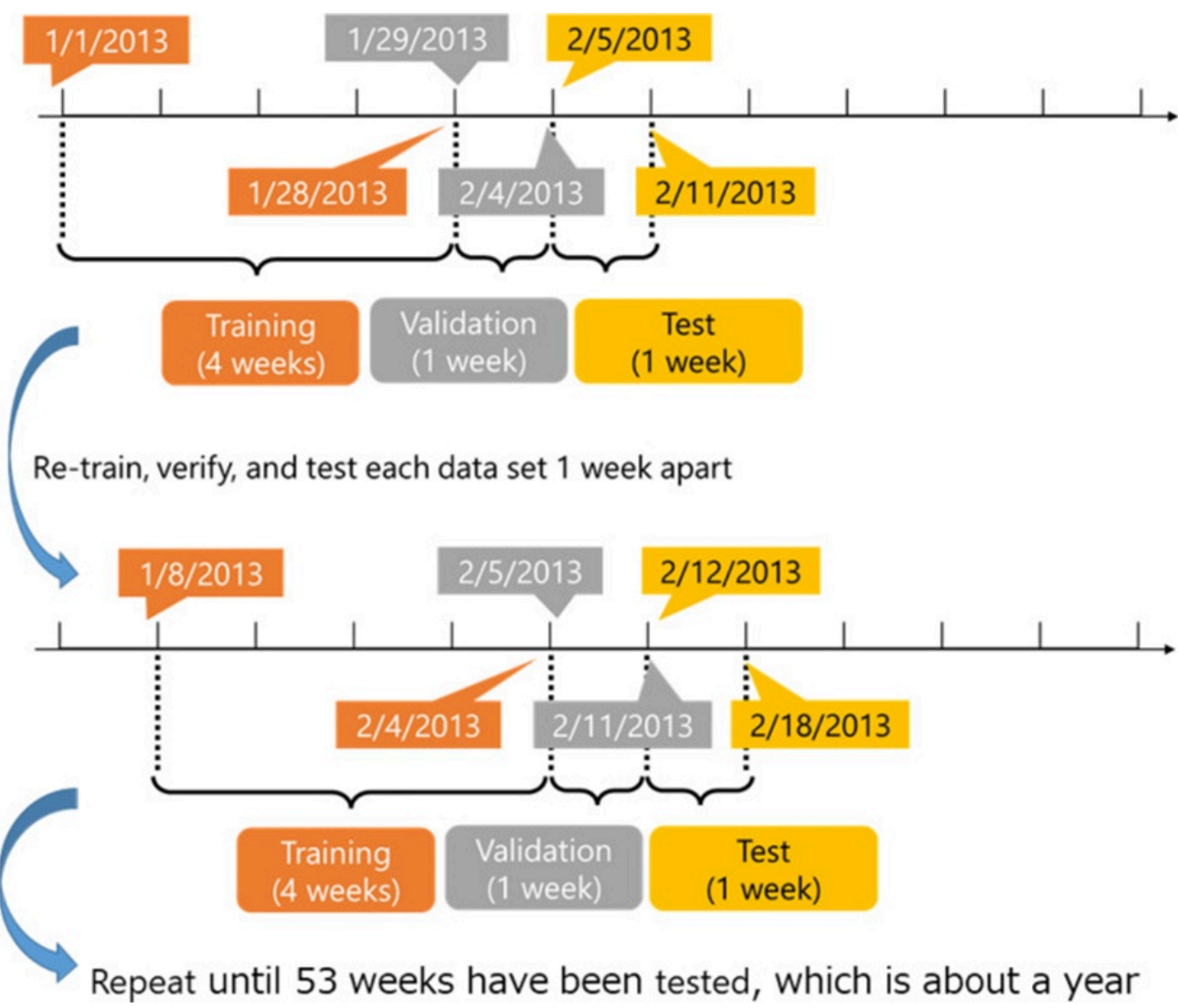


Figure 7. Details of experimental period.

Results

Table 1 reports the MAPE values calculated over the whole experimental timeframe for every mother wavelet setting. The row titled “switching to the best MW” reflects the situation in which the proposed method continuously adopts the mother wavelet that yields the strongest accuracy at each step. Essentially, this figure serves as the theoretical best-case performance achievable by the proposed method. **Table 1** clearly demonstrates that forecasting accuracy varies with the mother wavelet used for time-series decomposition. In addition, multiple configurations—including variants of the proposed method—deliver better results than db5, the mother wavelet applied in our previous research [20]. The strongest outcome was a MAPE of 2.148%, achieved by one version of the proposed method that selects the mother wavelet based on prediction performance over the prior three weeks. Still, the “switching MW (n = 3)” configuration fell short of the theoretical optimum (“switching to the best MW”) by approximately 0.07 percentage points. The factors contributing to this small shortfall are analyzed in the discussion that follows.

Figure 8a presents, for the dates July 22 to 23, the real electricity prices together with the forecasts generated under three conditions: a fixed db4 mother wavelet, a fixed sym5 mother wavelet, and the proposed dynamic switching approach. The vertical axis shows electricity price levels, and the horizontal axis indicates time using the “month-day hour” format. For the proposed method in **Figure 8a**, July 23 corresponds to the mother wavelet’s weekly transition point.

In other words, the method relies on db4 up through July 22 and then shifts to sym5 beginning on July 23, since sym5 had recorded the highest accuracy over the most recent three weeks. As **Figure 8a** illustrates, adopting sym5 from the week of the 23rd brings the predicted values noticeably closer to the actual prices compared with continuing to use a fixed db5. **Figure 8b** displays the absolute errors associated with each mother wavelet's predictions for the same timeframe shown in **Figure 8a**. From **Figure 8b**, it can be observed that while the proposed method registers a higher error at 7:00 on the 23rd, its errors are generally lower than those of the fixed db5 model at most other time points. This pattern indicates that updating the mother wavelet weekly based on recent forecasting outcomes effectively limits any major loss in accuracy.

Table 1. MAPE of each mother wavelet (MW) over the entire experimental period.

Mother wavelet	MAPE (%)	Description
Switching to the best MW	2.074660	Ideal scenario of the proposed method.
Switching MW (n = 3)	2.148150	Proposed method.
Switching MW (n = 8)	2.152941	
Switching MW (n = 6)	2.158812	
Switching MW (n = 9)	2.163366	
Switching MW (n = 5)	2.164564	
Switching MW (n = 7)	2.172413	
Switching MW (n = 10)	2.174297	
Switching MW (n = 4)	2.178161	
Switching MW (n = 2)	2.182103	
Symlet 5	2.196947	
Switching MW (n = 1)	2.206786	Proposed method.
Daubechies 4	2.212410	
Daubechies 6	2.295169	
Daubechies 5	2.307206	Employed in our prior work [20].
Symlet 4	2.399550	
Daubechies 3	2.445557	
Symlet 3	2.545998	
Daubechies 2	2.703441	
Daubechies 1	2.858116	

Figure 9a illustrates the MAPE values achieved by each mother wavelet every week, and **Figure 9b** displays the weekly ranking of those mother wavelets according to their forecasting performance. To improve readability, only selected time intervals are included, with the $n = 3$ configuration—which produced the best outcome in **Table 1**—serving as the representative case for the proposed method. Mother wavelets that surpassed the accuracy of db5 (the one adopted in

our earlier research) are highlighted using solid lines. In **Figure 9(a)**, the horizontal axis corresponds to successive weeks, and the vertical axis indicates the MAPE; lower values indicate greater accuracy. The chart shows that the proposed method (solid red line) effectively limits average error over a large number of weeks. A notable example occurs during the week of April 30 to May 6, where fixing the mother wavelet at db1 yielded a MAPE of 6.91%, but the proposed method lowered it to 3.95%. This corresponds to an accuracy gain of roughly 42.8%. In **Figure 9b**, the horizontal axis aligns with the weeks shown above. The vertical axis ranks the mother wavelets from best to worst by error magnitude, so a higher position on the chart indicates better performance. While many other mother wavelets drop to 15th place or below during certain weeks, the proposed method (solid red line) maintains a position of 4th or higher throughout.

Additionally, db5 unexpectedly ranked first during the weeks of April 2 to 8 and May 7 to 13. This sudden improvement accounts for the small gap between the proposed method's best result and the theoretical optimum observed in **Table 1**. Since the proposed method bases its selection on past performance, it cannot instantly incorporate a mother wavelet that becomes markedly superior in a single period.

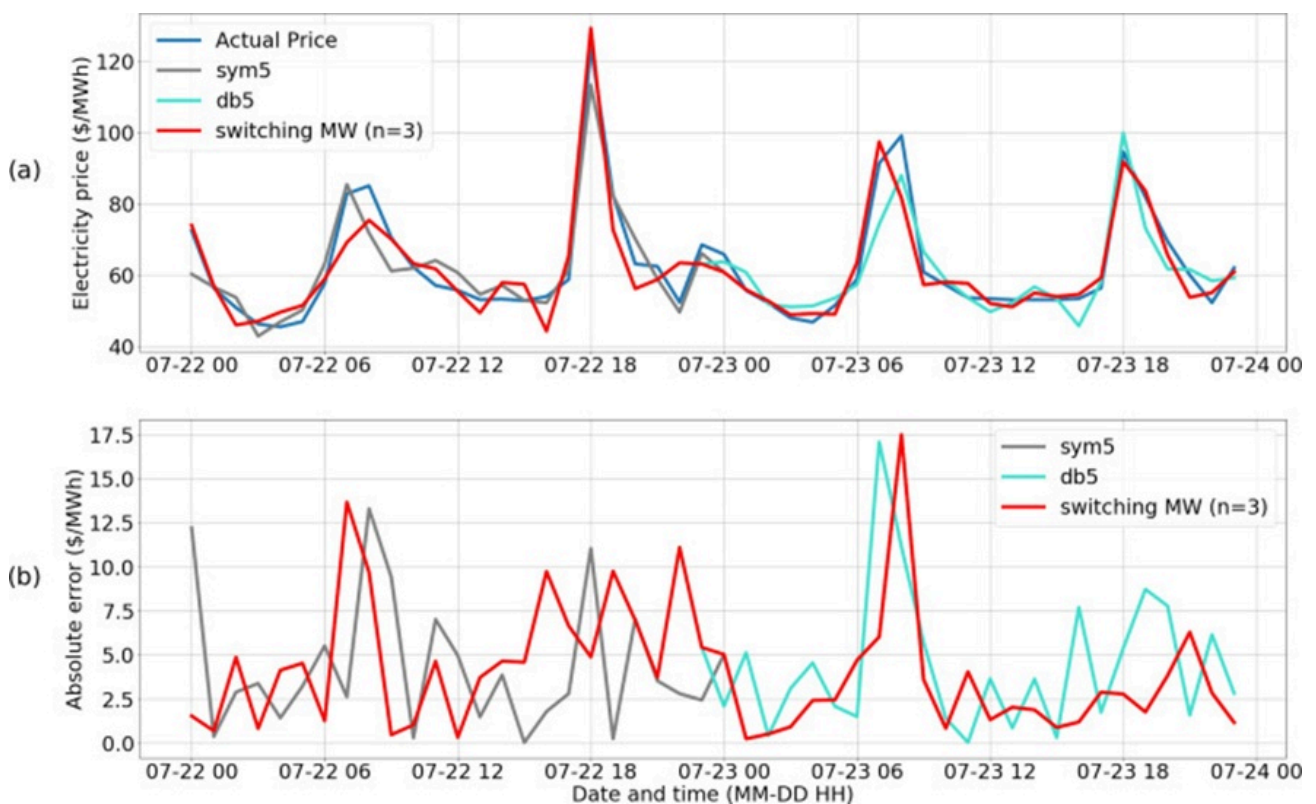


Figure 8. Predicted and actual prices for July 22–23 and absolute error for each mother wavelet.

Figure 10 presents the average accuracy ranking of each mother wavelet across the entire experimental timeframe, derived from the weekly results in **Figure 9**. Lower bars indicate better average rankings and therefore stronger overall accuracy. The figure confirms that the proposed method delivers higher average accuracy than the competing mother wavelets, extending beyond the excerpted periods shown in **Figure 9** to the entire study duration. Overall, these findings indicate that dynamically switching the mother wavelet helps mitigate week-by-week drops in forecasting quality.

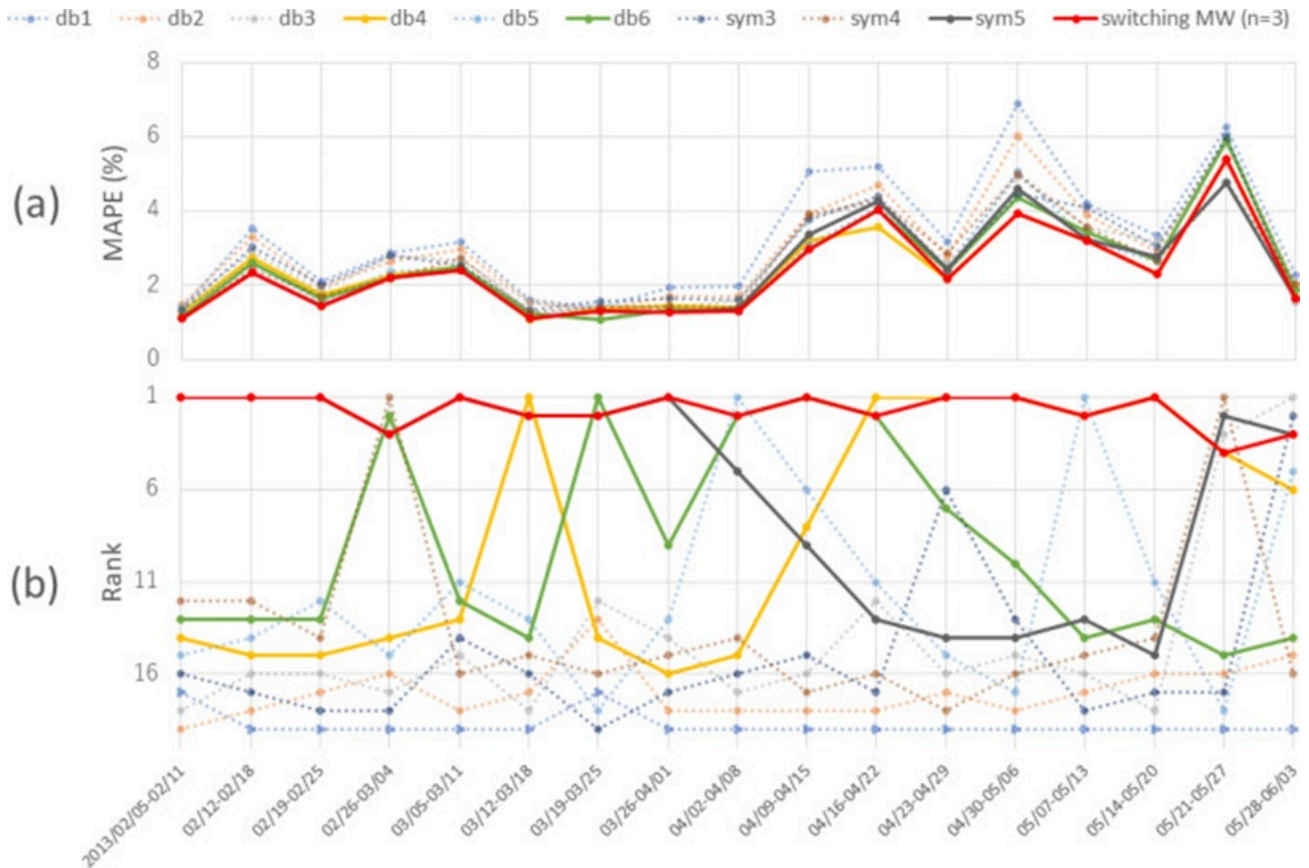


Figure 9. Prediction accuracy, MAPE, and rank for each mother wavelet by week.

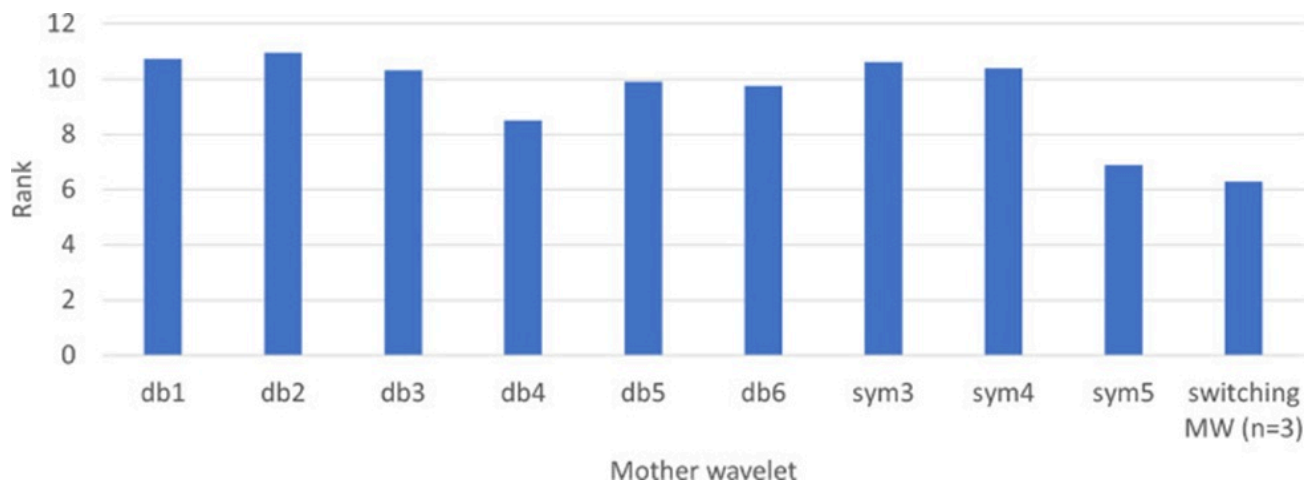


Figure 10. Average rank of accuracy over experimental period.

Conclusion

This paper presents a new electricity price forecasting model tailored for demand-side energy management in dynamic pricing systems. The model offers a clear improvement over the earlier hybrid approach that integrated a wavelet transform and Long Short-Term Memory using decomposed components of both price and demand data. In particular, the research targeted consistently high accuracy by periodically updating the mother wavelet, an essential adjustable parameter of the wavelet transform. The performance of the proposed model was tested through experiments using

hourly electricity price and demand records collected in New South Wales, Australia, during 2013. Accuracy levels were benchmarked across 19 distinct decomposition strategies: nine that kept a single mother wavelet fixed and ten that applied the proposed switching mechanism. When performing one-step-ahead prediction—estimating the price for the following hour at each hourly step—the proposed method consistently outperformed all fixed-mother-wavelet alternatives in both stability and precision. The top result emerged when the mother wavelet was updated according to the forecasting outcomes from the preceding three weeks. Across the experiment, the proposed method achieved a maximum error reduction of 42.8% relative to configurations using a constant mother wavelet. Future efforts will focus on embedding the developed forecasting model into existing energy management platforms to evaluate its real-world performance at the achieved accuracy level. Moreover, deploying the proposed forecasting model alongside a comprehensive energy management structure in actual operating environments will be crucial. In such practical deployments, further empirical analysis will determine how the model's reliable price predictions support optimized energy consumption on the demand side and influence electricity market operations.

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Conflict of interest

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