

Article

Green Power Price Forecast Based on Multi-Dimensional Taylor Network and Wavelet Method

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Abstract

Time series forecasting in power systems is crucial for power supply planning and exerts a direct impact on the electricity market. Accurate forecasting can effectively mitigate decision-making risks. This paper proposes a forecasting method based on a multi-dimensional Taylor network (MTN) and applies it to electricity price prediction. The time series is decomposed into one low-frequency signal and several high-frequency signals. The MTN model is constructed for each frequency sequence. The final forecast is obtained by aggregating the predictions from all frequency components. Using European electricity price data as a case study, experimental results demonstrate that the proposed method achieves high predictive accuracy.

Keywords: power price forecast; wavelet method; green computing; multi-dimensional Taylor network

1. Introduction

Power systems are integral to modern societal infrastructure and essential for maintaining normal social operations [1]. However, power pricing mechanisms are highly complex and often not fully understood, which motivates data-driven quantitative research [2]. Power systems generate vast amounts of data, which naturally form time series. The goal of such quantitative analysis is to develop models that can identify patterns within electricity price data and predict future trends [3].

In practice, time series often exhibit non-stationary and nonlinear characteristics. Its evolution can be regarded as the outcome of interactions among multiple variables. Electricity price time series, in particular, is a typical example of nonlinear time series [4]. From the data perspective, it has the characteristics of non-stationary, multi-peak and chaos.

The purpose of forecasting is to support decision-making and mitigate associated risks by providing estimates of future states; consequently, forecasting finds extensive application across numerous domains. In the power systems, time series prediction is directly applied to the planning of power generation and consumption, thereby significantly influencing system operations [5]. Furthermore, the power industry in many countries is undergoing increasing marketization and competition [6]. This trend reflects the importance of anticipating market dynamics to enable providers to deliver higher-quality, lower-cost services to both producers and consumers. Time series in power systems are characterized



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by high frequency, high volatility, calendar effects, and irregular patterns, among other features [7].

Research over the past years has yielded a variety of electricity price forecasting methods and theoretical conjectures, leading to significant advancements [8]. This article aims to critically examine the complexity, advantages, and limitations of existing approaches. Although the prediction algorithm has a long history, several challenges remain unresolved.

In many countries, electricity is traded as a commodity following market rules. However, electric energy is a unique commodity due to the economic challenges associated with its large-scale storage. Consequently, maintaining power system stability requires a continuous real-time balance between production and consumption [9]. Simultaneously, electricity demand is strongly influenced by factors such as weather conditions and the intensity of commercial activities. On the one hand, these distinctive characteristics result in electricity price dynamics that differ significantly from those of other commodities [10]. On the other hand, these complexities also motivate researchers to develop better forecasting techniques [11].

At the company level, electricity price forecasting serves as a critical input for strategic decision-making [12]. This is particularly crucial during economic crises, when power systems become highly vulnerable as retailers may struggle to directly pass on costs [13]. Excessive subcontracting and price fluctuations can lead to huge losses. Therefore, forecasting electricity prices from several hours to several months ahead has emerged as a prominent research topic. Utilizing forecast data to adjust production schedules or bidding strategies days in advance can enhance profitability significantly [14].

A review of the relevant literature allows for a classification of electricity price forecasting methods. Without loss of generality, these methods can be categorized into six primary models:

- 1 Multi-agent models: These simulate heterogeneous agents to replicate the pricing process by matching market demand with supply constraints [15];
- 2 Simulation element: These methods determine price dynamics by simulating the effects of physical or economic factors on electricity prices [16];
- 3 Simplified variables: This approach characterizes the statistical properties of electricity prices over time, with the ultimate goal of facilitating derivative valuation and risk management [17];
- 4 Statistical methods: This category primarily involves the direct application of statistical techniques from load forecasting or the implementation of econometric models within the energy market [18];
- 5 Intelligent technologies: These methods integrate elements such as learning and evolution to construct adaptive frameworks capable of handling complex dynamic systems [19];
- 6 Synthesis: Many methods presented in the literature represent a synthesis, combining one or more of the aforementioned approaches.

In recent years, the neural network method has seen significant advancements in recent years. As a mature modelling and control method, it is capable of addressing complex problems [20]. However, a primary drawback is that the computational burden increases geometrically with the number of neurons. Therefore, the multi-dimensional Taylor networks (MTN) has been proposed as an effective solution to mitigate the high computational demands of neural networks [21]. In recent years, MTN-based control has demonstrated promising results and has found widespread application across various domains. For example, MTN output-feedback tracking control for discrete-time nonlinear single-input single-output systems has been studied in the literature [22]. Similarly, a short-term traffic flow prediction method integrating wavelet transform (WT) with an

MTN is proposed in the literature [23]. There, WT is employed to decompose traffic flow time series, thereby enhancing prediction accuracy by mitigating the effects of short-term noise. Furthermore, aiming to achieve predetermined tracking performance for a class of nonlinear systems, an adaptive funnel control strategy utilizing an MTN is introduced in [24]. However, in the context of electricity price forecasting—characterized by uncertainty and nonlinearity—general methods often struggle to balance prediction accuracy with computational efficiency. Moreover, to the best of our knowledge, no prior research has explored the application of MTN specifically for electricity price forecasting.

Reference [25] proposes an explainable AI-based error compensation method to improve model performance and identify abnormal predictions. Reference [26] presents a novel hybrid reconstruction model based on Variational Mode Decomposition (VMD), Improved Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (ICEEM-DAN), Improved Grey Wolf Optimization (IGWO) and Long Short-Term Memory (LSTM) network. Reference [27] puts forward a new dynamic pricing framework suitable for electric vehicle charging stations, which can provide customers with a variety of charging options within a limited time horizon. However, such AI-based data prediction algorithms, although improved in data accuracy, inevitably require excessive computational complexity.

To bridge this gap, this paper proposes a dynamic modeling approach based on the multi-dimensional Taylor network. This approach treats electricity price fluctuations as a dynamic model and, when integrated with wavelet analysis, is applied to model and forecast European electricity price time series. The experimental results verify the effectiveness of the proposed method.

This article is organized as follows. Section 2 comprehensively describes the structure of the Multi-dimensional Taylor Network. The parameter adjustment algorithm is detailed in Section 3. Sections 4 and 5 introduce the wavelet decomposition and the time prediction model, respectively. Section 6 presents a case study to validate the proposed scheme, and Section 7 provides concluding remarks.

2. Establishment of Multi-Dimensional Taylor Network

The Multi-dimensional Taylor Network (MTN) possesses the capability of function approximation and can approximate any nonlinear function with a finite number of discontinuous points. Compared with other methods based on neural network, MTN has the following advantages: (1) its structure is transparent; (2) it excels at representing and approximating nonlinear dynamic systems; and (3) it involves only addition and multiplication operations, which simplifies computation and facilitates real-time control implementation. In addition, the MTN inherently constitutes a dynamic model, and function approximation can be achieved solely by adjusting its internal parameters.

Set

$$\mathbf{x}(k) = [x_1(k), x_2(k), \dots, x_n(k)] \quad (1)$$

The basic structure of MTN is depicted in Figure 1.

That is, there exists a set of parameter vectors such that the output of MTN $y_a(k)$ can be expressed as

$$y_a(k) = \sum_{j=1}^{N(n,l)} w_{aj}(k) \prod_{s=1}^n x_s^{\lambda_{s,j}}(k) \quad (2)$$

where $w_a = [w_{a1}, w_{a2}, \dots, w_{aN(n,l)}]$; $N(n, l)$ is the number of polynomials in the expansion; w_{aj} is the weight of the polynomial; $\lambda_{s,j}$ is the power of $x_s(k)$ in the j th product term, and $\sum_{s=1}^n \lambda_{s,j} \leq l$.

Set

$$E = \frac{1}{l} \sum_{i=1}^m \sum_{k=1}^l [y_{ai}^*(k) - y_{ai}(k)]^2 = \frac{1}{l} \sum_{i=1}^m \sum_{k=1}^l e_{ai}^2(k) \quad (5)$$

Then

$$w_{aj}(k+1) = w_{aj}(k) - \alpha_j(k) \frac{\partial E}{\partial w_{aj}(k)} \quad (6)$$

where $\frac{\partial E}{\partial w_{aj}(k)} = \sum_{i=1}^m \frac{\partial E}{\partial y_a(k)} \cdot \frac{\partial y_a(k)}{\partial w_{aj}(k)}$.

Since the underlying system structure is unknown, but the influence of the system output on the real system is accessible, the gradient term $\frac{\partial y_a(k)}{\partial w_{aj}(k)}$ can be approximated by its sign, represented by the symbolic function $\text{sgn}[\frac{y_a(k+1) - y_a(k)}{w_{aj}(k) - w_{aj}(k-1)}]$.

This substitution is feasible because the numerical value of $\frac{\partial y_a(k)}{\partial w_{aj}(k)}$ as an intermediate product term can be adjusted by step $\alpha_j(k)$, but this substitution does not change the direction of adjustment. Furthermore, this approach mitigates the potential issue of excessively large parameter updates that might occur due to rapid changes in consecutive input samples.

In addition, an adaptive adjustment strategy is adopted for the step size $\alpha_j(k)$:

Set

$$\alpha_j(0) = \alpha_{j0} \quad (7)$$

where α_{j0} is the given initial value.

And

$$\alpha_j(k+1) = \begin{cases} \beta \cdot \alpha_j(k) & \left\| \frac{\partial E}{\partial w_{aj}(k)} \right\| < \left\| \frac{\partial E}{\partial w_{aj}(k+1)} \right\| \\ \gamma \cdot \alpha_j(k) & \left\| \frac{\partial E}{\partial w_{aj}(k)} \right\| \geq \left\| \frac{\partial E}{\partial w_{aj}(k+1)} \right\| \end{cases} \quad (8)$$

where $\beta > 1$, $0 < \gamma < 1$, and $\left\| \frac{\partial E}{\partial w_{aj}(k)} \right\|$ is the norm of $\frac{\partial E}{\partial w_{aj}(k)}$. These two parameters are generally determined based on empirical experience. In the example presented in this paper, beta is set to 1.2 and gamma to 0.3. In general, larger values lead to faster convergence speed in the initial stage but may cause oscillations when the error is small.

4. Wavelet Decomposition

In recent years, wavelet transform theory has been extensively applied in data prediction and multi-time scale analysis. It has been successfully combined with various methodologies, including grey system theory, chaos theory, and neural networks, yielding promising results. The MTN model proposed in this paper serves as an equivalent dynamic model. Filtering and re-modeling the price time series across different timescales via wavelet decomposition can effectively suppress short-term noise disturbances while accentuating the long-term dynamic movement trends.

A wavelet is a waveform of finite duration that has a mean value of 0. Let $\theta(t)$ be a square integrable function, i.e., $\theta(t) \in L^2(R)$.

If the Fourier transform of $\theta(t)$ satisfies the condition

$$S_\theta = \int_R \frac{|\hat{\theta}(t)|^2}{|t|} dt < \infty \quad (9)$$

then $\theta(t)$ is termed a mother wavelet or wavelet basis function.

Wavelets exhibit two key characteristics: first, they possess a compact or approximately compact support in time domain; second, they exhibit oscillatory behavior (alternating between positive and negative values) due to a zero DC component. Whereas Fourier analysis decomposes a signal into a superposition of sine waves of different frequencies,

wavelet analysis decomposes a signal into a superposition of wavelet functions derived from a single mother wavelet through scaling and translation. By scaling and translating the wavelet mother function $\theta(t)$, the function $\theta_{\alpha,\omega}(t)$ can be obtained.

$$\theta_{\alpha,\omega}(t) = \alpha^{-\frac{1}{2}} \theta\left(\frac{t-\omega}{\alpha}\right), \alpha, \omega \in \mathbb{R}; \alpha > 0 \quad (10)$$

where α is the scaling factor and is the translation factor. The meaning of wavelet transform is to make the basic wavelet function $\theta(t)$ as the displacement of ω , and then do the inner product with the signal $f(t)$ to be analyzed under the α of different scales

$$WT_f(\alpha, \omega) = \langle f(t), \theta_{\alpha,\omega}(t) \rangle = \alpha^{-\frac{1}{2}} \int_{\mathbb{R}} f(t) \theta^*\left(\frac{t-\omega}{\alpha}\right) dt \quad (11)$$

For practical computation, the discrete wavelet transform (DWT) is employed, which involves discretizing both the scale and translation parameters.

Set $\alpha = \alpha_0^j$, $\omega = k\alpha_0^j\omega_0$, where $j, k \in \mathbb{Z}$, then the discrete wavelet function is

$$\theta_{j,k}(t) = \left(\frac{1}{\sqrt{\alpha}}\right)^j \theta(\alpha_0^{-\frac{j}{2}}t - k\omega_0) \quad (12)$$

The corresponding discrete wavelet transform is defined as:

$$WT_f(j, k) = \int f(t) \theta_{j,k}^*(t) dt \quad (13)$$

Multiresolution analysis provides a fundamental framework for wavelet analysis. On this basis, Mallat developed a fast algorithm for wavelet decomposition and reconstruction, known as the Mallat algorithm. In this algorithm, the original signal A is decomposed into the high-frequency part X_1 and low-frequency part D_1 through the filter, and the low frequency part D_1 can be further decomposed into X_2 and D_2 . In this case, after decomposition, the original signal A is decomposed into

$$A = X_1 + X_2 + \cdots + X_N + D_N \quad (14)$$

Each of the decomposed subsequences (approximations and details) is modeled, identified, and predicted independently. The forecasts for the original signal are then obtained by applying the inverse discrete wavelet transform to reconstruct the signal from the predicted components.

In our model and examples, we use the Daubechies wavelet (db4) as the mother wavelet. It should be noted that the type of mother wavelet has little influence on the final results, so the choice of wavelet function does not affect the validity and conclusions of the proposed method.

5. Time Prediction Model of Multi-Dimensional Taylor Network Based on Wavelet

The fluctuation of electricity prices, driven by various external factors, constitutes a continuous process in the market. Consequently, the underlying governing function can be regarded as asymptotically continuous when represented by a dynamic model, making it amenable to approximation by the MTN.

The proposed forecasting framework comprises the following steps. Firstly, the Mallat wavelet decomposition and reconstruction fast algorithm is used to decompose and reconstruct the pre-processed original time series $x(k)$ to form $N + 1$ sub-time series, including N high-frequency part $X_1 \sim X_N$ and a low-frequency part D_N . Next, phase

space reconstruction is applied to each of these one-dimensional sub-series to transform them into n dimensional state vectors. Subsequently, an MTN model is established for each embedded sub-series, its parameters are identified, and it is used to generate predictions for that component. Finally, the predictions for all individual components are aggregated through wavelet reconstruction to produce the final forecast for the original time series.

The whole process is illustrated in Figure 2.

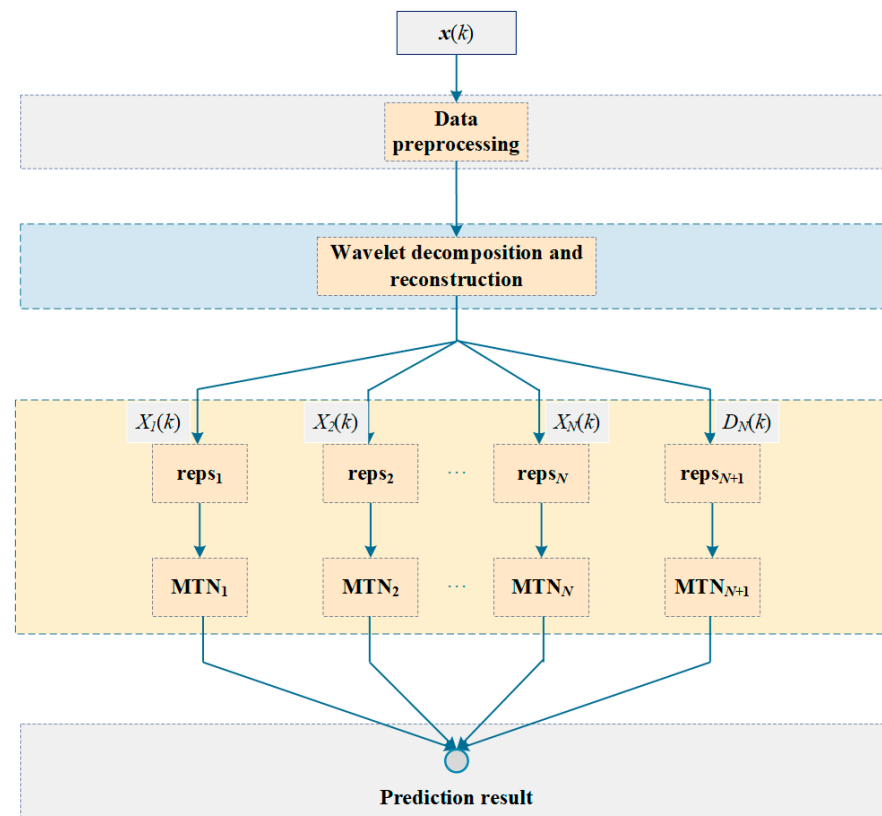


Figure 2. Prediction model framework based on wavelet MTN.

In the diagram, “RPS” denotes Phase Space Reconstruction. This step converts a one-dimensional time series into a set of multi-dimensional state vectors using a time delay embedding parameter $\tilde{\omega}$.

The embedding process is defined as follows:

$$x(k) = [x_1(k), x_2(k), \dots, x_n(k)] = [x(k), x(k - \tilde{\omega}), x(k - 2\tilde{\omega}), \dots, x(k - (n - 1)\tilde{\omega})] \quad (15)$$

Equation (15) implements space reconstruction via time-delay embedding, which transforms 1D wavelet-decomposed signals ($X_1, X_2, \dots, X_N, D_N$) into n -dimensional state vectors.

Specifically, the formula $x(k) = [x(k), x(k - \delta), x(k - 2\delta), \dots, x(k - (n - 1)\delta)]^T$ constructs a state vector at time k by concatenating the current signal value and its $n - 1$ historical values with a fixed time delay δ , where n denotes the embedding dimension and δ is the delay step.

This reconstruction uses historical data as input—i.e., previous state values—to capture temporal dynamics. By adopting the proposed basic model structure and optimizing its parameters, these structured state vectors are employed to realize subsequent data prediction.

6. Simulation Example

To validate the proposed model, a case study was conducted using 300 days of historical data from European electricity price markets (source: Nord Pool, <https://www.nordpoolgroup.com>, from 12 June 2022 to 17 April 2023, accessed on 10 December 2025). The first 270 data points were utilized as the training set, while the remaining 30 points were reserved for testing and validation.

The actual values and single-step predicted values of 30 test data are shown in Table 1.

Table 1. Comparison of actual values and single-step predicted values for 30 test data.

Serial Number	Actual Value	Predicted Value	Relative Error	Serial Number	Actual Value	Predicted Value	Relative Error
1	35.06	38.84	−10.80%	16	18.94	58.77	−210.28%
2	140.75	150.41	−6.86%	17	24.98	52.32	−109.46%
3	148.58	177.52	−19.47%	18	84.05	83.6	0.54%
4	143.32	143.21	0.07%	19	49.86	54.9	−10.10%
5	128.54	100.85	21.54%	20	150.43	122.48	18.58%
6	49.66	44.68	10.03%	21	127.81	135.11	−5.71%
7	36.86	6.29	82.93%	22	82.15	108.41	−31.97%
8	83.21	91.05	−9.42%	23	178.26	146.14	18.02%
9	110.89	130.62	−17.79%	24	181.82	175.03	3.74%
10	151.4	148.58	1.86%	25	152.13	150.88	0.82%
11	157.68	181.54	−15.13%	26	166.29	152.18	8.48%
12	162.27	151.98	6.34%	27	131.54	143.56	−9.14%
13	170.61	146.22	14.29%	28	53.68	90.28	−68.19%
14	111.73	82.99	25.72%	29	44.6	43.99	1.37%
15	13.17	10.46	20.58%	30	95	109.85	−15.63%

A visual comparison between the actual price curve and the predictions generated by the W-MTN model is presented in Figure 3.

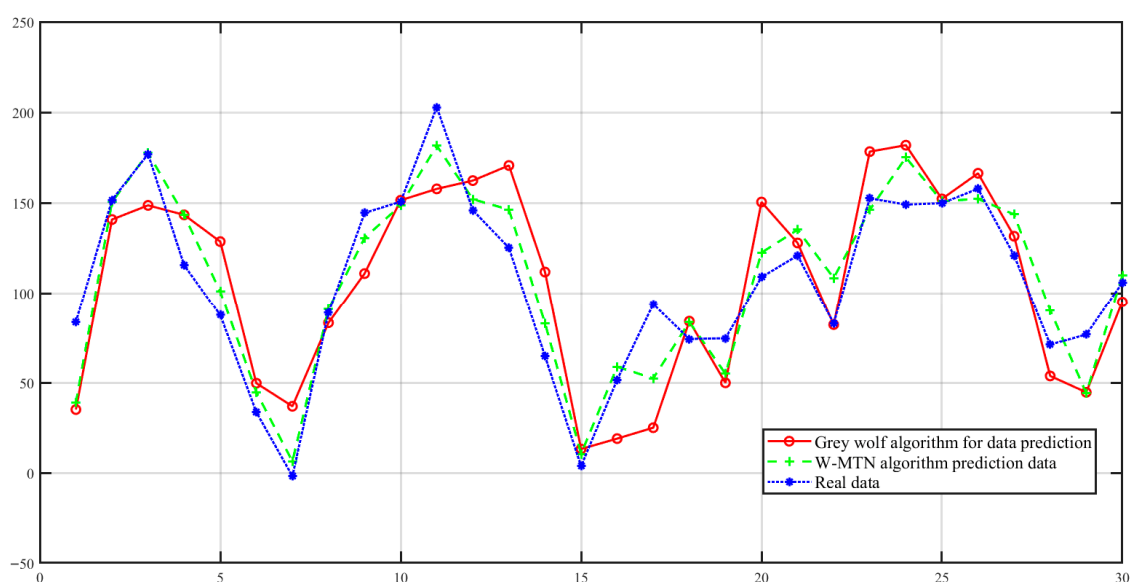


Figure 3. Data prediction chart based on W-MTN.

To objectively evaluate the forecasting capability of the proposed W-MTN model, its performance was benchmarked against three alternative models: a standard Artificial Neural Network (ANN), a MTN, and a Wavelet-ANN (W-ANN) model. The error index

and prediction ability of each model are processed. The number of layers of the neural network is 3; the number of nodes is (3, 3, 1); the number of iterations is 1000; and stop threshold 1×10^{-4} . The calculation results are summarized in Table 2.

Table 2. Error comparison.

Prediction Model	RMSE	MAE	MAPE
ANN	29.86	23.73	43.5658%
MTN	26.80	21.31	36.4198%
W-ANN	29.99	24.69	42.5755%
W-MTN	20.08	15.95	25.8299%
GWOA	22.27	18.15	30.3104%

The index RMSE (root mean square error), MAE (mean absolute error) and MAPE (mean absolute percentage error) quantitatively assess prediction accuracy, where lower values indicate superior forecasting performance.

As evidenced by the results in Table 2, the ANN and MTN models exhibit comparable forecasting performance, with the MTN holding a marginal advantage. While the integration of wavelet decomposition yielded only a slight performance improvement for the W-ANN model over the standard ANN, the enhancement achieved by the W-MTN model over the baseline MTN is substantially more pronounced. For comparative analysis, the Grey Wolf Optimizer (GWO), a swarm intelligence algorithm mimicking the hierarchical hunting behavior of grey wolves, is also implemented. In this study, the GWO is configured with a population size of 30, a maximum of 100 iterations, and a convergence factor a that decreases linearly from 2 to 0. The algorithm iteratively updates the positions of the three leading wolves (α , β , δ) to guide the swarm toward the optimal solution, thereby identifying the best hyperparameters for the prediction model. The experimental results show that the GWO achieves competitive forecasting accuracy, with RMSE, MAE, and MAPE values of 22.27, 18.15, and 30.3104%, respectively. Although the GWO outperforms the ANN, MTN, and W-ANN models, it is still surpassed by the W-MTN model, which attains the lowest error metrics across all indicators. This finding confirms that the proposed framework, which combines wavelet decomposition with the multi-dimensional Taylor network, constructs a more robust and accurate forecasting model than the standalone optimization-based GWO approach.

The efficacy of wavelet decomposition for electricity price forecasting can be attributed to the multi-factorial nature of price formation. Unlike typical physical dynamic systems, electricity prices are heavily influenced by anthropogenic factors. While individual factors may exhibit randomness and be inherently difficult to predict, their collective superposition forms a dynamic process from which underlying patterns can be extracted. Wavelet decomposition separates the time series into distinct frequency components. The low-frequency approximation captures the long-term dynamic trend, while the high-frequency details represent short-term fluctuations, often containing unstable transients and random noise. Modeling these components separately effectively mitigates the impact of short-term noise and reinforces the dominant long-term trend in the final forecast.

In the ANN model, neuron outputs are typically constrained by activation functions (e.g., sigmoid). Consequently, when modeling system dynamics, ANNs tend to attenuate non-smooth signal components. This makes them more suitable for systems with gradual state changes. For volatile signals like electricity prices, the high-frequency detail components obtained from wavelet decomposition are prone to being suppressed by these activation functions. The resultant loss of high-frequency information can cause the model's output to fail in tracking rapid changes present in the input signal. Generally, ANNs are

often more naturally suited for classification tasks than for time series forecasting. In contrast, the MTN model expresses system dynamics more generically by establishing a dynamic state equation. When integrated with wavelet decomposition, the MTN can effectively extract and model the dynamic characteristics inherent in different frequency signals. This fundamental architectural advantage explains the superior performance of the W-MTN model over the W-ANN model.

The number of wavelet decomposition layers is a critical parameter influencing both final prediction accuracy and computational efficiency. Figure 4 shows this example model when the number of wavelet decomposition layers is from 1 to 7, the prediction index MAPE curve (Layer 1 corresponds to no decomposition; Layer 2 yields one high-frequency detail and one low-frequency approximation; Layer 3 yields two details and one approximation, and so forth.) As observed in Figure 4, with the increase in the number of decomposition layers, the prediction effect increases significantly at first, and then stabilizes in a certain range with small irregular fluctuations. This phenomenon can be explained as follows. The electricity price time series contains substantial random noise. As the decomposition level increases, the amplitude of the newly isolated high-frequency components diminishes, and their stochastic nature becomes more pronounced. Modeling and predicting these fine-scale, highly random components introduces unpredictable positive and negative contributions to the aggregate forecast. Therefore, the observed performance fluctuates irregularly. However, due to the small amplitude of these deepest high-frequency components, their net impact on the final prediction is limited. Based on the empirical results presented in Figure 4, selecting 2 or 3 decomposition layers represents an optimal trade-off for this application.

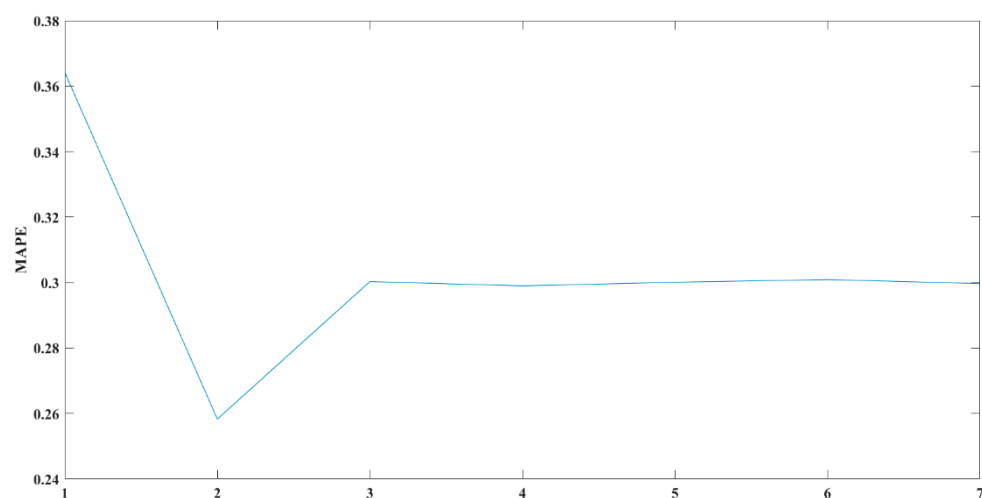


Figure 4. Relation Diagram of MAPE and Wavelet decomposition layers.

Regarding the sample size and potential overfitting: The structure of each Multi-Dimensional Taylor Network (MTN) is relatively compact, with 3 inputs, a maximum polynomial order of 2, and only 10 polynomial terms in the basic structure. Since all MTNs share the same lightweight architecture and only the polynomial coefficients need to be identified, the total number of trainable parameters is considerably small compared with deep neural networks.

During the experiments, we have tested cases with more than three input variables and polynomial orders higher than 2. According to the experimental results, when the dataset is limited, more inputs or higher orders do not necessarily lead to better performance. Moreover, as the number of inputs and the polynomial order increase, the number of polynomials grows geometrically, which results in a rapid increase in computational cost.

Therefore, we choose three input variables and second-order polynomial as the optimal configuration to achieve a good balance between accuracy and computational complexity. The multi-dimensional Taylor network is mainly used to model unknown systems using input and output data. The best performance is achieved when the network order matches or is close to the actual system order. However, the proposed method has certain limitations when dealing with purely random time series.

With a total of 270 samples, the data volume is sufficient for training such a parameter-efficient dynamic model. In addition, wavelet decomposition is applied to filter short-term noise and separate multi-scale components, which further simplifies modeling difficulty and effectively suppresses overfitting. During training, we also adopted reasonable validation and parameter optimization strategies to ensure generalization performance. Experimental results demonstrate that the model achieves good fitting accuracy without obvious overfitting.

7. Conclusions

This paper has presented a novel forecasting method for electricity price time series by integrating wavelet decomposition with the Multi-dimensional Taylor Network (MTN). Experimental results, evaluated through metrics such as prediction accuracy and directional accuracy, demonstrate the feasibility and effectiveness of the proposed approach. Furthermore, this study validates the feasibility of applying the MTN model to general dynamic system modeling. Future work will focus on exploring the model's applicability to a wider range of domains and complex scenarios.

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References

1. Liang, J.; Zhao, D.; Qiu, L. Feedback Stability Under Mixed Gain and Phase Uncertainty. *IEEE Trans. Autom. Control* **2025**, *70*, 1008–1023. [\[CrossRef\]](#)
2. Yang, H.; Wang, L.; Zhang, Y.; Tai, H.-M.; Ma, Y.; Zhou, M. Reliability Evaluation of Power System Considering Time of Use Electricity Pricing. *IEEE Trans. Power Syst.* **2019**, *34*, 1991–2002. [\[CrossRef\]](#)
3. Wang, J.; Jin, X.; Jia, H.; Tostado-Véliz, M.; Mu, Y.; Yu, X.; Liang, S. Joint Electricity and Carbon Sharing with PV and Energy Storage: A Low-Carbon DR-Based Game Theoretic Approach. *IEEE Trans. Sustain. Energy* **2024**, *15*, 2703–2717. [\[CrossRef\]](#)
4. Lu, J.; Zeng, D.; Zheng, Y.; Yan, F.; Tang, Y. Fault Prediction of Electromagnetic Launch System Based on Knowledge Prediction Time Series. *IEEE Trans. Ind. Appl.* **2020**, *57*, 1830–1839. [\[CrossRef\]](#)
5. Zeng, D.; Lu, J.; Zheng, Y. Combined Fuzzy Time Series Prediction Method for Fault Prediction of EML Pulse Capacitors. *IEEE Trans. Plasma Sci.* **2021**, *49*, 905–913. [\[CrossRef\]](#)
6. Liang, X.; Hofman, J. Trip Curves and Ride-Through Evaluation for Power Electronic Devices in Power System Dynamic Studies. *IEEE Trans. Ind. Appl.* **2015**, *52*, 1290–1296. [\[CrossRef\]](#)
7. Li, H.; Yeo, J.H.; Bornsheuer, A.L.; Overbye, T.J. The Creation and Validation of Load Time Series for Synthetic Electric Power Systems. *IEEE Trans. Power Syst.* **2020**, *36*, 961–969. [\[CrossRef\]](#)
8. Corrêa, G.V.; Nascimento, C.D.D.; Souza, E.G. Advanced Modal Identification of Local Electromechanical Transients via the Modified Complex Morlet Wavelet Transform. *IEEE Trans. Ind. Appl.* **2025**, *61*, 8089–8099. [\[CrossRef\]](#)
9. Xu, J.; Liao, S.; Sun, Y.; Ma, X.-Y.; Gao, W.; Li, X.; Gu, J.; Dong, J.; Zhou, M. An Isolated Industrial Power System Driven by Wind-Coal Power for Aluminum Productions: A Case Study of Frequency Control. *IEEE Trans. Power Syst.* **2014**, *30*, 471–483. [\[CrossRef\]](#)
10. Ruibal, C.M.; Mazumdar, M. Forecasting the Mean and the Variance of Electricity Prices in Deregulated Markets. *IEEE Trans. Power Syst.* **2008**, *23*, 25–32. [\[CrossRef\]](#)
11. Yin, J.; Zhan, X. Impact of Bias-Correction Methods on Effectiveness of Assimilating SMAP Soil Moisture Data into NCEP Global Forecast System Using the Ensemble Kalman Filter. *IEEE Geosci. Remote Sens. Lett.* **2018**, *15*, 659–663. [\[CrossRef\]](#)
12. Wan, C.; Ming, N.; Song, Y.; Niu, M.; Song, Y.; Xu, Z. Pareto Optimal Prediction Intervals of Electricity Price. *IEEE Trans. Power Syst.* **2017**, *32*, 817–819. [\[CrossRef\]](#)
13. Kirschen, D.S.; Strbac, G.; Cumperayot, P.; Mendes, D.d.P. Factoring the elasticity of demand in electricity prices. *IEEE Trans. Power Syst.* **2000**, *15*, 612–617. [\[CrossRef\]](#)
14. Anbazhagan, S.; Kumarappan, N. Day-Ahead Deregulated Electricity Market Price Forecasting Using Recurrent Neural Network. *IEEE Syst. J.* **2013**, *7*, 866–872. [\[CrossRef\]](#)
15. Wehinger, L.; Hug-Glanzmann, G.; Galus, M.D.; Andersson, G. Modeling electricity wholesale markets with model predictive and profit maximizing agents. *IEEE Trans. Power Syst.* **2013**, *28*, 868–876. [\[CrossRef\]](#)
16. Xiao, C.; Sutanto, D.; Muttaqi, K.M.; Zhang, M. Online Sequential Extreme Learning Machine Algorithm for Better Prediction of the Real-time Electricity Price under Dynamic Environmental Changes. In *Proceedings of the 2019 IEEE Industry Applications Society Annual Meeting, Baltimore, MD, USA, 29 September–3 October 2019*; IEEE: New York, NY, USA, 2019.
17. Zhao, Z.; Wu, L.; Song, G. Convergence of Volatile Power Markets with Price-Based Demand Response. *IEEE Trans. Power Syst.* **2014**, *29*, 2107–2118. [\[CrossRef\]](#)
18. Yu, R.; Yang, W.; Rahardja, S. A Statistical Demand-Price Model with Its Application in Optimal Real-Time Price. *Smart Grid IEEE Trans.* **2012**, *3*, 1734–1742. [\[CrossRef\]](#)
19. Shrivastava, N.A.; Khosravi, A.; Panigrahi, B.K. Prediction Interval Estimation of Electricity Prices Using PSO-Tuned Support Vector Machines. *IEEE Trans. Ind. Inform.* **2015**, *11*, 322–331. [\[CrossRef\]](#)
20. Kobayashi, M. Quaternion Projection Rule for Rotor Hopfield Neural Networks. *IEEE Trans. Neural Netw. Learn. Syst.* **2020**, *32*, 900–908. [\[CrossRef\]](#) [\[PubMed\]](#)
21. Yan, H.S.; Duan, Z.Y. Tube-Based Model Predictive Control Using Multidimensional Taylor Network for Nonlinear Time-Delay Systems. *IEEE Trans. Autom. Control* **2020**, *66*, 2099–2114. [\[CrossRef\]](#)
22. Sun, Q.M.; Yan, H.S. Multi-dimensional Taylor network modelling and optimal control of SISO nonlinear systems for tracking by output feedback. *IMA J. Math. Control Inf.* **2019**, *37*, 699–717. [\[CrossRef\]](#)
23. Zhu, S.; Zhao, Y.; Zhang, Y.; Li, Q.; Wang, W.; Yang, S. Short-Term Traffic Flow Prediction with Wavelet and Multi-Dimensional Taylor Network Model. *IEEE Trans. Intell. Transp. Syst.* **2020**, *22*, 3203–3208. [\[CrossRef\]](#)
24. Zhu, S.L.; Duan, D.Y.; Chu, L.; Wang, M.-X.; Han, Y.-Q.; Xiong, P.-C. Adaptive multi-dimensional Taylor network tracking control for a class of switched nonlinear systems with input nonlinearity. *Trans. Inst. Meas. Control* **2020**, *42*, 2482–2491. [\[CrossRef\]](#)
25. Heistrene, L.; Belikov, J.; Baimel, D.; Katzir, L.; Machlev, R.; Levy, K.; Mannor, S.; Levron, Y. An Improved and Explainable Electricity Price Forecasting Model via SHAP-Based Error Compensation Approach. *IEEE Trans. Artif. Intell.* **2025**, *6*, 159–168. [\[CrossRef\]](#)

26. Zhu, A.; Zhao, Q.; Yang, T.; Zhou, L. A Novel Hybrid Model Based on Secondary Decomposition and Artificial Intelligence Approach for Abnormal Data Reconstruction. *IEEE Trans. Consum. Electron.* **2025**, *71*, 3431–3441. [[CrossRef](#)]
27. Zhao, Z.; Lee, C.K.M. Dynamic Pricing for EV Charging Stations: A Deep Reinforcement Learning Approach. *IEEE Trans. Transp. Electrification*. **2022**, *8*, 2456–2468. [[CrossRef](#)]

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