



Short Term Electricity Price Forecasting based on Optimal Spike Interval Prediction

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ARTICLE INFO	ABSTRACT
Article type: Research Paper Article History: Received 28 May 2026 Accepted 7 September 2026 Keywords: Electricity price spike forecasting, input data model, Lower bound of price, Upper bound of price, optimization algorithm.	Increasing competition among electricity market players (mainly generation companies [GenCos]) emphasizes the significance of well-maintained operational planning, risk management, and decision-making. Electricity price forecasting plays a critical role in this respect. However, forecasting electricity prices is a complex and challenging task because price signals are nonlinear, non-stationary, and time-varying. Price fluctuations in power markets are both periodic and random, with price spikes being examples of events that severely affect forecasting performance. Although many forecasting methods have been proposed, few forecasting methods focus specifically on price spike information. There are two major challenges in price spike forecasting: predicting when a spike will occur and how large it will be. A typical assumption is that neural network (NN) information about expected future data points is equally valuable, or even more valuable. Prediction is mainly treated using an online NN approach. This paper proposes a novel approach for forecasting both the occurrence and value of electricity price spikes. The developed method is based on an improved neural network-based algorithm that calculates the upper and lower bounds of the price signal. Compared to traditional techniques, the proposed approach predicts both the price spike class and intensity in a single step. The method was evaluated using real data from several electricity markets. The obtained results indicate the accuracy and efficiency of the proposed method. The proposed method achieves up to 98% spike occurrence prediction accuracy (PJM 2006, \$150/MWh threshold) and 96.9% (PJM 2008), correctly identifying most price spikes in real market data.
Cite this article:	Bahrampour, N. (2026). Short Term Electricity Price Forecasting based on Optimal Spike Interval Prediction. <i>Energy Systems: Technology and Management</i>, 2 (1), 69-78. DOI: http://doi.org/10.48306/estm.2026.583453.1019.



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DOI: <http://doi.org/10.48306/estm.2026.583453.1019>.

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1. Introduction

The monopoly on electricity had been, for many years, exclusively in the hands of the state. This structure underwent a fundamental change from monopoly to competitive electricity market with the introduction of competition factoring in the broader generation sector inputs into the electricity industry. Consequently, electricity is viewed as a core driver in environment such as bilateral and pool-based exchanges and the exchange of electricity price [1]. And in that sort of environment, the price is not set, but rather a result of participants and interactions between power supply and demand. Producers and retailers compete in exchanging the power produced, power requirements on each hourly basis and also providing a price-based bid to consumers. Price has high volatility and risk in such an environment. Producers and retailers need an accurate forecast of price for planning, investment, operation and risk management purposes for the future [2]. Price forecasting is also essential for Generation companies (GenCos), large retailers of electricity and distribution companies (DisCos) in a competitive market to identify their bid strategy, realistically maximize their profit through asset allocation, obtaining bilateral agreements, overcoming risk and investment planning. Price forecasting is essential for an independent system operator (ISO) (which adapts GenCo's bid and its consumers) to enhance its performance [3]. Within price forecasting, many different methods have been proposed. We group these techniques into time-series, statistical, and AI-based methods. Transfer function models [4], dynamic regression models [5], Auto-Regressive Integrated Moving Average (ARIMA) models [6], and Generalized Auto-Regressive Conditional Heteroskedastic (GARCH) models [7] form the spectrum of time-series-based modeling methods. They are typically parametric and linear models. On the other hand, AI models are usually non-linear and

non-parametric. Such methods include artificial neural networks (ANNs) [8], fuzzy inference systems (FISs) [9], and support vector machines (SVMs) [10].

Spikes are characteristic of electricity price, which affect the accuracy of predictions. Spikes can also have serious economic consequences for market participants. Generally, price spikes are unusual prices at time t , which are significantly different from prices at time $t-1$, and their value is often 3 to 20 times bigger than usual prices. In total, spike forecasting has two main aspects: 1- spike occurrence forecasting, and 2- spike-values forecasting. In the first section, it determines that when a spike occurs, and in the second section, the value of this spike is forecasted. In data-mining methods, these two stages are divided into two separate problems. Spike occurrence prediction is a classification problem in which the target is a binary vector of zero and one values that determines whether a spike will occur or not. On the other hand, spike value prediction is a regression problem which its aim is the continuous determination of price at any time [11].

However, electricity price spike forecasting is a complicated task. Many price forecasting techniques focus on regular price forecasting rather than spike forecasting. In [12] a framework based on data mining has been proposed for both normal and spike electricity price forecasting. The normal price has been predicted by a wavelet and neural network based forecast model, and the spikes have been forecasted based on a data mining technique. In [13] two algorithms, support vector machine and probability classifier, were used to predict both occurrence and value of price spikes. Authors in [11] proposed a novel technique which integrates spike forecasting with decision making. This technique is based on Naïve Bayesian classifier. A regime-switching model has been proposed in [14] for price spike forecasting.

Ref. [15] developed a time-varying probability Markov switching model for price

spike forecasting of Queensland electricity market. Ref. [16] suggested using temperature instead of the information on load or the reserve margin for price spike forecasting. A new technique consisting of a modern hybrid data model, a novel feature-selection technique, and a probabilistic neural network as the forecasting engine was proposed in [23] for price-spike occurrence prediction. In [17], a new strategy is proposed for both price spike occurrence and value prediction. In this reference, a probabilistic neural network was employed for occurrence and a hybrid neuro-evolutionary system (HNES) for value prediction. In [18], Australia's national electricity market spot prices have been modeled with the neural network. Based on the neural-network results, price spikes were identified using extreme-value modeling. Then a generalized Pareto distribution was then fitted for spikes higher than a threshold. Ref. [19] examined electricity prices from a system-dynamics perspective and proposed a hybrid model combining a recurrent neural network (RNN) with a coupled excitable system. Combining an RNN with a coupled excitable system made it possible to forecast time series containing price spikes. Rastgoo et al. proposed a spike-aware deep learning framework based on variational auto-encoders to improve electricity price spike prediction under severe class imbalance conditions [20]. Zhang et al. developed a hybrid CatBoost–XGBoost model for short-term electricity price forecasting, demonstrating improved accuracy in volatile market environments through ensemble learning strategies [21]. Jaimes et al. proposed a hybrid LSTM–XGBoost stacking approach for multi-day electricity price forecasting with explicit spike handling mechanisms to enhance prediction reliability in deregulated markets [22]. Sheybanivaziri et al. provided a comprehensive review of electricity price spike forecasting methods and highlighted the increasing use of probabilistic and machine learning approaches for modeling extreme events in electricity markets [23]. Zhong et al. developed an integrated ANN–LSTM–Transformer framework for electricity price forecasting, showing that attention-based

deep learning architectures can further improve forecasting accuracy in highly volatile markets [24].

Prediction Intervals (PIs) provide more information about the level of uncertainties in the power system. Prediction intervals consist of two bounds (upper and lower) which include the actual price with a predefined probability, named confidence level.

In this paper, first, the proposed method for PIs construction in [25] is developed, and it is used to construct bounds (upper and lower) for price signal, then the constructed PIs of price plus historical price builds a hybrid data model for NN input. The hybrid data is refined by a two-step feature selection technique, and a minimum subset of best inputs is obtained. NN is trained with this data model and forecasts both occurrence and value of price spikes in one step.

The rest of the paper is organized as follows: Section 2 explains electricity price spike. Section 3 explains the developed technique to construct bounds of the price. The proposed technique for price spike forecasting is described in Section 4. In order to evaluate the accuracy of the proposed technique, some criteria are defined in Section 5. Section 6 presents the numerical results. Finally, the paper is concluded in Section 7.

2. Electricity Price Spike

In the first step, we need a threshold to separate price spikes from normal prices, so the prices higher than this threshold are considered spikes. The threshold of μ in [13] has been considered for this purpose, that μ and σ are mean and standard deviation of historical prices, respectively. Different power markets have different thresholds [13]. For example, Ref. [12], it is discussed that in California electricity market, maximum threshold of price is 50 \$/MWh, and the threshold of 75 \$/MWh has been proposed for the Queensland electricity market. In [26], thresholds of 150 and 200 \$/MWh have been considered for PJM electricity market.

3. Developed Technique For PIs Construction

In [27], a new technique is proposed for Prediction Intervals (PIs) construction. This technique, which is based on a neural network, is called "Lower Upper Bound Estimation (LUBE)". Moreover, it is a fast and reliable technique for PIs construction. The LUBE method is an NN with two outputs, which corresponds to the upper and lower bounds.

In the prediction intervals construction process, intervals should cover the main price signal with high probability and they should have a narrow width as far as possible. Therefore, high coverage probability and low interval width are two objectives in PIs construction problem which are against each other. The reference [27] proposes a single objective function which covers these two objectives. The NN should be trained through minimization of this objective function. Since this function is not differentiable, NN training is done through an evolutionary algorithm. In [27], Simulated Annealing (SA) has been used for this purpose.

Here, this technique is developed to construct PIs with higher coverage probability and lower interval width. First, the NN with two outputs is trained by Levenberg–Marquardt training algorithm. These outputs are the replicas of the target (electricity price). In fact, the target is repeated and the two outputs are similar. The NN is trained using this target and the trainLM algorithm. Then, the NN with these optimized weights and biases is trained based on minimization of the single objective function. Particle Swarm Optimization (PSO) is used as the evolutionary algorithm for NN training in the second stage. The first step (training NN with trainLM) provides PSO with a good starting point and increase its efficiency. For more information about PIs construction, the reader is referred to [27].

4. The Proposed Technique for Price Spike Forecasting

With respect to most of the research on spike forecasting, there are two main aspects in

which prediction is used: spike occurrence and spike value. Some studies have only predicted spike occurrence as a binary value [28], while others have first forecasted the occurrence and then, according to the two different behaviors of spikes and non-spikes, used different forecasting engines for each one [17]. The one-step forecasting approach proposed in this paper predicts both spike occurrence and the value of price spikes using the proposed techniques. Figure 1 illustrates the workflow of the proposed model.

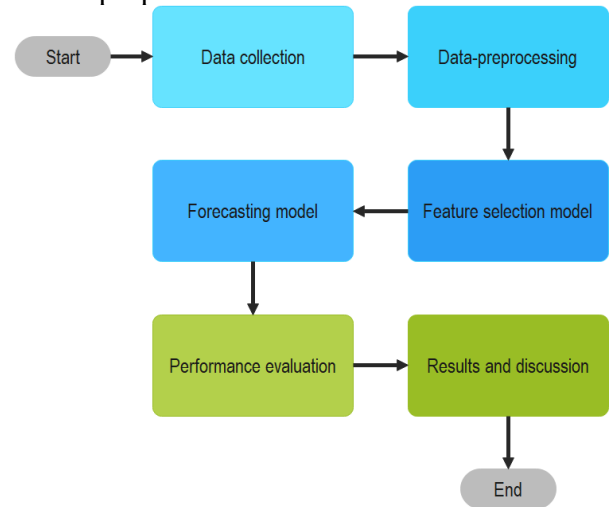


Fig. 1. Flowchart illustrating the workflow of the proposed model.

The structure of the newly proposed method for price spike forecasting is illustrated in Figure 2. As shown, the framework consists of three main components: a hybrid input data model, a two-step feature selection method, and an efficient neural network as the forecasting engine. The proposed data model constructs a set of input candidates for the forecasting task. This set is then iteratively reduced by the two-stage feature selection process until the minimum number of the most informative inputs is selected. The selected inputs are then fed into the neural network for the prediction process.

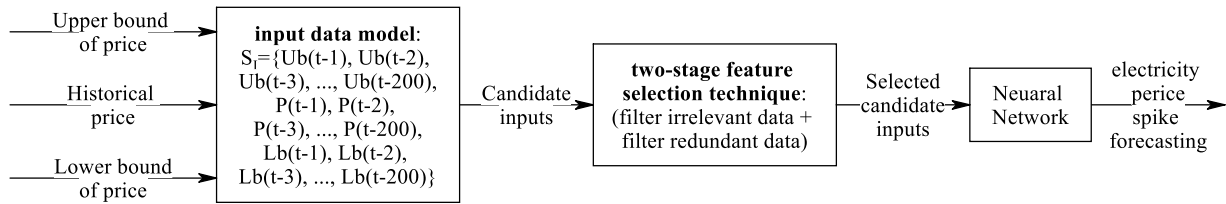


Fig. 2. Structure of the proposed technique for price spikes forecasting.

The neural network output, which is the forecasted signal of price, is checked. If the forecasted price is higher than the predetermined spike threshold, the forecasted price is classified as a spike, and its value is obvious, but if the forecasted price is lower than the threshold, the forecasted price is not a spike. In this way, both spike occurrence and value are predicted in one step.

4.1. The Input Data Model

The novelty of the proposed technique for spike forecasting is the use of the upper and lower bounds of price for spike forecasting. In forecasting problems, first, the input data according to the target should be determined. Here, the input data of the upper and lower bound of price, and historical price for spike forecasting are used.

Training the neural network is done using one year of data preceding the test day; it means that for NN, training $365 \times 24 = 8760$ training samples are used. The forecasting horizon is 24 hours ahead. To determine whether spikes will occur on the following, first, the neural network is trained with selected features and 8760 training samples, the day immediately following the training period is then forecasted. Among the 24-hourly forecasts (NN output), prices higher than the specified threshold for the spike, are classified as spikes for the following day.

The historical price is obtained from the data of any electricity market, but for upper and lower bounds of price, which are the other candidate inputs; we constructed these bounds by using the developed technique in section 3 for PIs construction. Since the one-year data before the test day is required for training, PIs should be constructed for one year. Therefore, PIs are constructed for one year of each

electricity market which its spikes should be forecasted with the developed technique for PIs construction. In other words, 8760 data for upper bound of price and 8760 data for lower bound of price are constructed at first.

4.2. Construction of the Training and Target Matrices

For neural network training to forecast the price, two matrices are required as inputs to the NN, which are called training and target matrices. The target matrix is a single row vector that contains the value of forecasting target (electricity prices).

Each column of the training matrix is a training sample. In the present study, the training samples are: upper bound, price and lower bound. The number of training samples for spike forecasting in this paper is one year ago ($24 \times 365 = 8760$ training samples).

Each row of the training matrix represents previous values of the target row. In other words, the first row of the training matrix is the prices one hour before the target and so on. These values which are called "lagged values" are important. In [33, 34] has been discussed that price time series has daily and weekly periodicity, and to consider this issue, lagged values have been considered to 200 hours ago. It means that the rows of the training matrix correspond to lagged values from 1 to 200 hours before the target. Since for spike forecasting in this paper, we use upper and lower bounds and historical price, the training matrix has 600 rows (200-hour upper bounds before target value, 200-hour prices before target values, and 200-hour lower bounds before target values). The candidate input data set for spike forecasting, which is shown in Figure 1, is as follows:

$S = Ub(t-1), Ub(t-2), Ub(t-3), \dots, Ub(t-200), P(t-1), P(t-2), P(t-3), \dots, P(t-200), Lb(t-1), Lb(t-2), Lb(t-3), \dots, Lb(t-200)$

That Ub is upper bound and Lb is lower bound of price, which are constructed with developed PIs construction technique. Therefore, the training matrix is a 600×8760 matrix.

4.3. Effective Feature Selection for Forecasting Model

Forecasting accuracy is largely depends on a better feature selection for the neural network. Furthermore, input patterns with the greatest impact and high dependence may give better forecasting results in spite of the fact that there is no principle for feature selection in a forecasting model. An appropriate feature selection can happen based on engineering expertise or technical experience. Some statistical and dependency analyses can be useful for determining inputs, which significantly increase the forecasting accuracy.

NN training with 600 inputs is very time consuming and has a high computational cost, while the existence of irrelevant and redundant inputs causes high forecasting error. Therefore, an

efficient technique is required to select powerful features for training. Here, we use a two-stage feature selection technique based on Mutual Information (MI) as an effective technique for feature selection, which was proposed in [28].

4.4. Structure of the Neural Network

The structure of the neural network is very important. For example, if transfer functions and input variables are selected appropriately, a good forecast is obtained. In this paper, a two-layer feed forward back propagation neural network with trainLM has been used. The number of neurons in the hidden layer is determined based on selected features and a cross-validation mechanism which is introduced in [29]. The transfer function of the hidden layer is "tansig" and the output layer is "pureline".

5. Evaluating the Accuracy of Spike Occurrence and Value Forecasting

To evaluate the ability of spike occurrence forecasting, defining some criteria is required. The most famous criterion for classification tasks is "classification accuracy", which is defined as follows:

$$\text{Classification accuracy} = \frac{\text{number of test samples that have been classified correctly}}{\text{number of test samples}} \quad (1)$$

However, this criterion is not very appropriate for spike occurrence prediction, because the data of the problem is unbalanced. Therefore, a new criterion is required to evaluate the occurrence prediction better. For this purpose, two criteria have been defined in [11] that are used in this paper. These two criteria are: "spike prediction accuracy" and "spike prediction confidence" that are in percent and defined as follows:

$$\text{Spike prediction accuracy (\%)} = \frac{\text{number of correctly forecasted spikes}}{\text{number of spikes}} \quad (2)$$

$$\text{Spike prediction confidence (\%)} = \frac{\text{number of correctly forecasted spikes}}{\text{number of forecasted spikes}} \quad (3)$$

Spike prediction accuracy is a measure of the proportion of correctly predicted spikes. Meanwhile, a classification method might mistakenly categorize some non-spike points as spikes. This kind of mistake of the spike occurrence forecasting method can be measured by spike prediction confidence. The spike value prediction error of the proposed method is evaluated using the well-known error metric "Mean Absolute Percentage Error

(MAPE)", since both spike and normal prices are continuous variables.

Numerical Results

The new technique for price spike forecasting has been examined using real data of PJM day-ahead electricity market [30]. The test data used are shown in Table 1. Numerical experiments are designed to evaluate the effect of the hybrid input data model on the forecast model.

Spike occurrence prediction results with the proposed technique for the test data presented in Table 1 are presented in Tables 2 and 3. Ref. [28] forecasted spike occurrence using a two-stage feature selection and probabilistic neural network as the forecast engine for price data of PJM electricity market in the year 2006. Furthermore, Ref. [24] has forecasted both spike occurrence and value for price data from PJM electricity market in the year 2008. Spike occurrence forecasting results with the proposed technique and comparison with the results of these two references are presented in Tables 2 and 3.

In these tables, the first row is the specified spike threshold. The second row is the number of spikes in the test period in price data. The number of correctly predicted spike occurrence, which are the points that were not the spikes in real data and the proposed technique also forecasted as spikes, has been presented in the third row. The difference between the second and third rows is the number of spikes that the proposed technique did not forecast the occurrence of them. Some points that were not spikes, the model has forecasted those points as the spikes, the number of these points is presented in the fourth row with the title of "number of incorrect predictions". Spike occurrence prediction accuracy which is a classification problem, is calculated with Equation 2. In this equation, the number of correctly forecasted spikes is the third row of the table, and the number of spikes is the second row. If the proposed technique forecasts some non-spike points as spike, these numbers have presented in the fourth row, and the spike prediction confidence criterion is for this purpose. To calculate the spike prediction confidence,

Equation 3 is used. In this equation, the number of correctly forecasted spikes is the third row of the table, and the number of forecasted spikes is the summation of the third and fourth rows. For example, if we want to calculate the two mentioned criteria for spike occurrence prediction results for test data from PJM market in the year 2006, spike prediction accuracy is equal to, and spike prediction confidence is equal to $49/(49+1)=98\%$.

Tables 4 and 5 show the obtained results from the proposed technique for price spike forecasting. In these tables for each week over the test years, the number of spikes of that week, the number of correctly predicted spikes with the model and the number of incorrectly predicted spikes have been presented. Furthermore, in each week, the MAPE has been presented. Two spike thresholds have been considered for the PJM market. In these tables only the threshold of 150\$/MWh has been presented. The MAPE for each week at both thresholds (150 and 200) is equivalent because according to the proposed technique in section 4, the prediction is done by the model initially and then according to the specified thresholds, spikes are separated. Therefore, MAPE for each week in every threshold is the same. Average of MAPE for all year of 2006 is 2.5022% and 2008 is 3.4555% for the PJM electricity market.

In [17], spike occurrence and value prediction, has been done with a new strategy using price data from the PJM electricity market in the year 2008. The reported MAPE values in this reference for spike value forecasting for thresholds of 150 and 200 are 16.1% and 19%, respectively, and the corresponding values for normal-price forecasting are 9.2% and 8.9%. A Comparison these results with the reported results of the proposed technique (Table 5) indicates the better performance of the proposed technique for price spike forecasting. Figure 3 shows the real and forecasted signal of price for August 1, 2006, a day containing nine spikes and Figure 4 shows the real and forecasted signal of price for July 18, 2008, that contains nine spikes.

Table 1. Description of the test data for PJM electricity market with two spike thresholds (150 and 200).

Test period	Train period	Number of training samples	Number of test samples in each forecast day	Price spike threshold (\$/MWh)	Number of spikes in each test period
Year 2006	One year before forecast day	365*24=8760	24	150	50
Year 2008		366*24=8784			192
Year 2006		365*24=8760		200	25
Year 2008		366*24=8784			35

Table 2. Spike occurrence prediction results with proposed technique for test data of PJM electricity market (2006).

	PJM2006		Proposed technique		Ref.[23]	
Spike threshold (\$/MWh)			150	200	150	200
Number of spikes			50	25	73	25
Number of correct occurrence forecasts			49	23	71	23
Number of incorrect occurrence forecasts			1	1	10	3
Spike prediction accuracy (%)			98	92	97.3	92.0
Spike prediction confidence (%)			98	95.83	87.7	88.5

Table 3. Spike occurrence prediction results with proposed technique for test data of PJM electricity market (2008).

	PJM2008		Proposed technique		Ref.[24]	
Spike threshold (\$/MWh)			150	200	150	200
Number of spikes			192	35	192	35
Number of correct occurrence forecasts			186	33	184	30
Number of incorrect occurrence forecasts			9	2	15	6
Spike prediction accuracy (%)			96.875	94.286	95.8	85.7
Spike prediction confidence (%)			95.385	94.286	92.5	83.3

Table 4. Obtained results from the proposed technique for each week of year 2006 in PJM market (results are for threshold of 150 \$/MWh).

Week	Results*	Week	Results*	Week	Results*	Week	Results*
1	0,0,0,3.5652	14	0,0,0,3.2877	27	0,0,0,2.6619	40	0,0,0,1.4395
2	0,0,0,2.4152	15	0,0,0,2.7033	28	0,0,0,2.1593	41	0,0,0,1.1849
3	0,0,0,3.2894	16	0,0,0,2.2322	29	9,9,0,3.7755	42	0,0,0,1.8395
4	0,0,0,2.1235	17	0,0,0,1.3837	30	0,0,0,3.5237	43	0,0,0,2.6575
5	0,0,0,2.8599	18	0,0,0,1.4291	31	41,40,1,4.1406	44	0,0,0,2.991
6	0,0,0,1.9622	19	0,0,0,2.4524	32	0,0,0,3.7216	45	0,0,0,2.2932
7	0,0,0,2.3035	20	0,0,0,1.2604	33	0,0,0,3.7896	46	0,0,0,3.4946
8	0,0,0,2.2263	21	0,0,0,1.2881	34	0,0,0,2.8277	47	0,0,0,3.4085
9	0,0,0,1.3048	22	0,0,0,2.0408	35	0,0,0,2.2497	48	0,0,0,2.4829
10	0,0,0,2.3935	23	0,0,0,2.0974	36	0,0,0,3.3584	49	0,0,0,3.6261
11	0,0,0,2.012	24	0,0,0,1.5507	37	0,0,0,2.7586	50	0,0,0,2.5606
12	0,0,0,3.186	25	0,0,0,3.6009	38	0,0,0,1.5618	51	0,0,0,2.6601
13	0,0,0,2.8478	26	0,0,0,3.03	39	0,0,0,1.1831	52	0,0,0,1.9127

*Results: Number of spikes, Number of correct predictions, Number of incorrect predictions, MAPE(%)

Table 5. Obtained results from the proposed technique for each week of year 2008 in PJM market (results are for threshold of 150 \$/MWh).

Week	Results*	Week	Results*	Week	Results*	Week	Results*
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1	6,5,1,4.1511	14	0,0,0,3.7846	27	10,9,1,4.189	40	0,0,0,1.8513
2	0,0,0,4.5364	15	0,0,0,3.7771	28	22,22,0,4.411	41	0,0,0,1.3943
3	0,0,0,3.4693	16	0,0,0,2.4805	29	31,30,1,4.68	42	0,0,0,1.6036
4	0,0,0,3.3582	17	0,0,0,3.9378	30	17,17,0,5.21	43	0,0,0,1.8129
5	0,0,0,3.0072	18	0,0,0,3.6491	31	11,11,1,5.13	44	0,0,0,2.971
6	0,0,0,3.1535	19	0,0,0,4.9257	32	1,1,0,4.11	45	0,0,0,2.4077
7	0,0,0,3.311	20	0,0,0,4.0658	33	0,0,0,3.1662	46	0,0,0,1.891
8	0,0,0,3.4897	21	0,0,0,4.6396	34	0,0,0,3.2485	47	0,0,0,2.3648
9	0,0,0,2.7909	22	0,0,0,4.1149	35	0,0,0,4.1045	48	0,0,0,2.974
10	0,0,0,2.8031	23	16,16,0,5.1339	36	0,0,0,4.3848	49	0,0,0,2.9062
11	0,0,0,3.9041	24	51,49,3,5.85	37	0,0,0,2.3744	50	0,0,0,1.926
12	0,0,0,3.8351	25	4,3,0,5.674	38	0,0,0,3.2057	51	0,0,0,1.943
13	0,0,0,3.8605	26	23,23,2,4.518	39	0,0,0,2.0934	52	0,0,0,3.1132

*Results: Number of spikes, Number of correct predictions, Number of incorrect predictions, MAPE(%)

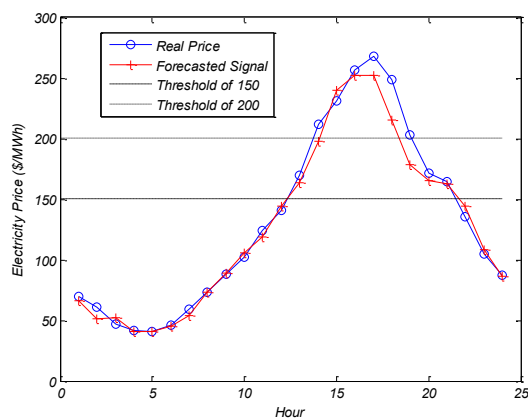


Fig. 3. Real and forecasted signal of price with the proposed technique for August 1, 2006, (MAPE=4.9865%).

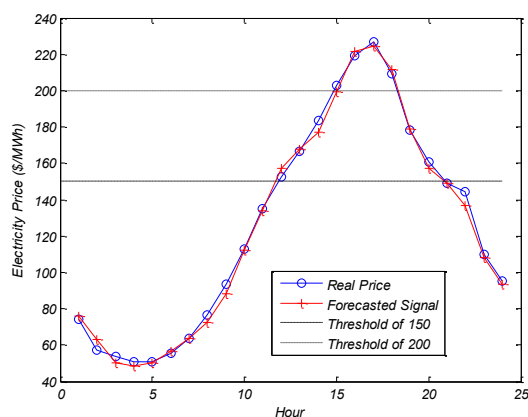


Fig. 4. Real and forecasted signal of price with the proposed technique for July 18, 2008, (MAPE=2.4979%).

7. Conclusion

Price forecasting is an important issue in electricity markets. Accurate and reliable

forecasting is necessary to facilitate participant decisions. Spikes are a common problem in power markets, which affect forecasting accuracy. Electricity spike forecasting is a complex task, and most of the methods have focused on normal price forecasting. Input variables to the forecast model are important and can improve the forecast accuracy. In this paper, a novel hybrid data model was proposed for neural network input to forecast price spikes. The modern data model is composed of upper and lower bounds of prices and historical prices. The bounds of prices were constructed with a developed version of a technique which is called "Lower Upper Bound Estimation". An effective neural network was used as the forecast engine. If the forecasted prices in the NN output are higher than the specified threshold for spikes, the forecasted point is classified as a spike. The proposed technique forecasted both price spike occurrence and value in one step. Real world data of electricity market were examined to indicate the good performance of the proposed technique.

References

- [1] J. Yang, Y., Guo, J. E., Li, Y., & Zhou, "Forecasting day-ahead electricity prices with spatial dependence," *Int. J. Forecast.*, vol. 40, no. 3, pp. 1255–1270, 2024.
- [2] C. Amountzias, H. Dagdeviren, and T. Patokos, "Pricing decisions and market power in the uk electricity market: A VECM approach," *Energy Policy*, vol. 108, no. June, pp. 467–473, 2017, doi: 10.1016/j.enpol.2017.06.016.

- [3] S. Soleymani, A. M. Ranjbar, and A. R. Shirani, "New approach for strategic bidding of Gencos in energy and spinning reserve markets," *Energy Convers. Manag.*, vol. 48, no. 7, pp. 2044–2052, Jul. 2007, doi: 10.1016/J.ENCONMAN.2007.01.002.
- [4] F. J. Nogales and A. J. Conejo, "Electricity price forecasting through transfer function models," *Journal of the Operational Research Society*, vol. 57, no. 4, pp. 350–356, Apr. 2006, doi: 10.1057/palgrave.jors.2601995.
- [5] F. J. Nogales, J. Contreras, A. J. Conejo, and R. Espínola, "Forecasting next-day electricity prices by time series models," *IEEE Transactions on Power Systems*, vol. 17, no. 2, pp. 342–348, 2002, doi: 10.1109/TPWRS.2002.1007902.
- [6] A. J. Conejo, M. A. Plazas, R. Espinola, and A. B. Molina, "Day-Ahead Electricity Price Forecasting Using the Wavelet Transform and ARIMA Models," *IEEE Transactions on Power Systems*, vol. 20, no. 2, pp. 1035–1042, 2005, doi: 10.1109/TPWRS.2005.846054.
- [7] "A GARCH forecasting model to predict day-ahead electricity prices".
- [8] N. M. Pindoriya, S. N. Singh, and S. K. Singh, "An Adaptive Wavelet Neural Network-Based Energy Price Forecasting in Electricity Markets," *IEEE Transactions on Power Systems*, vol. 23, no. 3, pp. 1423–1432, 2008.
- [9] G. Li, C.-C. Liu, C. Mattson, and J. Lawarrée, "Day-ahead electricity price forecasting in a grid environment," *Power Systems, IEEE Transactions on*, vol. 22, no. 1, pp. 266–274, 2007, doi: 10.1109/TPWRS.2006.887893.
- [10] "A Statistical Approach for Interval Forecasting of the Electricity Price".
- [11] J. H. Zhao, Z. Y. Dong, and X. Li, "Electricity market price spike forecasting and decision making," *IET Generation, Transmission & Distribution*, vol. 1, no. 4, pp. 647–654, Jul. 2007, doi: 10.1049/iet-gtd:20060217.
- [12] X. Lu, Z. Y. Dong, and X. Li, "Electricity market price spike forecast with data mining techniques," *Electric Power Systems Research*, vol. 73, no. 1, pp. 19–29, Jan. 2005, doi: 10.1016/j.epsr.2004.06.002.
- [13] J. H. Zhao, Z. Y. Dong, X. Li, and K. P. Wong, "A Framework for Electricity Price Spike Analysis With Advanced Data Mining Methods," *IEEE Transactions on Power Systems*, vol. 22, no. 1, pp. 376–385, Feb. 2007, doi: 10.1109/TPWRS.2006.889139.
- [14] T. D. Mount, Y. Ning, and X. Cai, "Predicting price spikes in electricity markets using a regime-switching model with time-varying parameters," *Energy Econ.*, vol. 28, no. 1, pp. 62–80, Jan. 2006, doi: 10.1016/j.eneco.2005.09.008.
- [15] R. BECKER, S. HURN, and V. PAVLOV, "Modelling Spikes in Electricity Prices*," *Economic Record*, vol. 83, no. 263, pp. 371–382, Dec. 2007, doi: 10.1111/j.1475-4932.2007.00427.x.
- [16] R. Huisman, "The influence of temperature on spike probability in day-ahead power prices," *Energy Econ.*, vol. 30, no. 5, pp. 2697–2704, Sep. 2008, doi: 10.1016/j.eneco.2008.05.007.
- [17] F. Amjady, N., & Keynia, "A new prediction strategy for price spike forecasting of day-ahead electricity markets," *Appl. Soft Comput.*, vol. 11, no. 6, pp. 4246–4256.
- [18] P. Dev and M. A. Martin, "Using neural networks and extreme value distributions to model electricity pool prices: Evidence from the Australian National Electricity Market 1998–2013," *Energy Convers. Manag.*, vol. 84, pp. 122–132, Aug. 2014, doi: 10.1016/j.enconman.2014.04.012.
- [19] V. Sharma and D. Srinivasan, "A hybrid intelligent model based on recurrent neural networks and excitable dynamics for price prediction in deregulated electricity market," *Eng. Appl. Artif. Intell.*, vol. 26, no. 5–6, pp. 1562–1574, May 2013, doi: 10.1016/j.engappai.2012.12.012.
- [20] A. Khosravi, S. Nahavandi, D. Creighton, and A. F. Atiya, "Lower upper bound estimation method for construction of neural network-based prediction intervals.," *IEEE transactions on neural networks / a publication of the IEEE Neural Networks Council*, vol. 22, no. 3, pp. 337–346, 2011, doi: 10.1109/TNN.2010.2096824.
- [21] N. Amjady and F. Keynia, "Day-ahead price forecasting of electricity markets by mutual information technique and cascaded neuro-evolutionary algorithm," *IEEE Transactions on Power Systems*, vol. 24, no. 1, pp. 306–318, 2008.
- [22] A. Khosravi, S. Nahavandi, D. Creighton, and A. F. Atiya, "Lower upper bound estimation method for construction of neural network-based prediction intervals," *IEEE Trans. Neural Netw.*, vol. 22, no. 3, pp. 337–346, 2011, doi: 10.1109/TNN.2010.2096824.
- [23] Nima Amjady and Farshid Keynia, "Electricity market price spike analysis by a hybrid data model and feature selection technique".
- [24] F. Keynia, "A new feature selection algorithm and composite neural network for electricity price forecasting," *Eng. Appl. Artif. Intell.*, vol. 25, no. 8, pp. 1687–1697, 2012, doi: 10.1016/j.engappai.2011.12.001.
- [25] PJM Web Site, "http://www.pjm.com."