Day-Ahead Electricity Spike Price Forecasting Using a Hybrid Neural Network-Based Method

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Abstract. A hybrid neural network-based method is presented to predict day-ahead electricity spike prices in a deregulated electricity market. First, prediction of day-ahead electricity prices is carried out by a neural network along with pre-processing data mining techniques. Second, a classifier is used to separate the forecasted prices into normal and spike prices. Third, a second neural network is trained over spike hours with selected features and is used to forecast day-ahead spike prices. Forecasted spike and normal prices are combined to produce the complete day-ahead hourly electricity price forecasting. Numerical experiments demonstrate that the proposed method can significantly improve the forecasting accuracy.

Keywords: Neural network · Price spikes · Day-ahead forecasting · Electricity market

1 Introduction

A competitive generation sector and open access to transmission systems are two common aspects of various competitive electricity markets around the world. However, depending on the market design and organization of the different electricity markets, there is considerable diversity in implementation. The competitive electricity markets from different jurisdictions may be categorized as single settlement markets or as two or multi-settlement markets [1]. The single settlement market is also known as a real time market in which the electricity prices are settled on hourly, half-hourly, or five minute bases depending on the demand and available supply. On the other hand, in a two settlement or multi-settlement market, settlement of prices for demand and supply depends on day-ahead and real-time operation of the market. In a two settlement market, prices are determined by a forward market for day-ahead consumption and generation of electricity and a real time market which is used to cover the differences between the proposed and actual consumption and generation. The problem of price spikes has been reported in almost all the electricity markets around the world. The main reason for the price spikes is the complexities and uncertainties in the power grid

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[2]. However, the severe nature of the occurrence of spikes may differ depending on the structure and operation of a market.

Price forecasting is important to power suppliers for short-term and medium-term planning in setting rational offers and signing bilateral contracts. Moreover, electricity prices in the open market greatly influence generation expansion plans in long-term planning. Therefore, forecasting of electricity prices is an important and challenging task and has gained momentum during recent years [3, 4]. Accurate forecasting of electricity prices is very useful for generators and consumers to determine their offers and bidding strategies. In the case of load management programs, independent system operators (ISOs) and large wholesale consumers can use forecasting information to look for reliable options to reduce system demand and high electricity prices during peak hours.

In this study, the Ontario wholesale electricity market is explored. The Ontario electricity market is interconnected with the neighbouring electricity markets of New York, New England, Midwest, and Pennsylvania-New Jersey-Maryland (PJM) [5, 6]. It is considered to be one of the most volatile electricity markets in the world due to its single settlement operation [7]. The occurrences of price spikes depend upon the volatile nature of the market. Hence, price forecasting in the Ontario electricity market is challenging.

The problem of price spike forecasting has been studied for different electricity markets of the world, using various methods. Most of these studies use support vector machine (SVM) and neural networks (NNs) [8–11]. In Zhao *et al.* [8], occurrences of price spikes from the national electricity market (NEM) in Australia are predicted using a support vector machine and probability classifier. These predicted spikes are combined with normal price forecasts to generate the overall price forecasting. Amjady and Keynia [9] report a wavelet transform method to construct the set of candidate inputs along with feature selection techniques for the forecasting process and probabilistic neural network (PNN) has been used to predict price spikes for the Queensland and PJM electricity markets. In Baez-Rivera *et al.* [10], price spike forecasting of the PJM electricity market is obtained by using radial basis neural networks. In a study by Wu *et al.* [11], the occurrence of price spikes for a regional electricity market in China is predicted with a Bayesian expert classifier while day-ahead hourly spikes are forecasted using SVM and artificial neural networks.

In addition to SVM and NNs, Christensen *et al.* [12] uses an autoregressive conditional hazard (ACH) model to forecast half-hourly ahead price spikes in the NEM Australia. Eichler *et al.* [13] extend the work by Christensen *et al.* [12] and employ a dynamic logit model to represent price spike forecasting for the NEM Australia. Lu *et al.* [2] and Zhao *et al.* [14] utilize a statistical approach to identify spikes and data mining techniques for spike forecasting for the NEM Australia. Although many studies have demonstrated good work on price spike forecasting, a significant improvement in forecasting accuracy is still needed. Furthermore, most of the studies for price spike forecasting have been carried out for the Australian electricity market, and no study on price spike forecasting for the Ontario wholesale electricity market has been reported. As pointed out by Zareipour *et al.* [7], the Ontario electricity market operates in real time only and is very volatile. Accordingly, the main objective of this paper is to develop techniques to forecast day-ahead spike prices for the Ontario electricity market with high forecasting accuracy.

In recent studies, neural network techniques have gained popularity for handling non-linear relationships accurately. Neural networks do not need prior information and depend on the processing of available data. Neural networks are capable of handling large classes of functions and are known as universal approximation models [15]. In this paper, a hybrid method based on neural networks and data mining techniques at the pre-processing stage is used to predict day-ahead price spikes and combined with the forecasted normal prices to achieve overall day-ahead price forecasting. Many features are responsible for variations in electricity prices. Some of these important features are demand, temperature, humidity, time of consumption, and type of generation facility available. In the current study, normal prices are forecasted with a method proposed by Sandhu *et al.* [16]. In the next step, a second neural network is trained over spike hours prior to the forecasting day in the same year and from the previous two years with data values of demand, temperature, dew point temperature and relative humidity. Spike prices over these hours are used as respective target values to compare the forecasted and actual values. Hence, day-ahead spike forecasting is achieved with reduced errors with this trained neural network. The first neural network used to forecast the normal prices in Sandhu *et al.* [16] is called as Network 1 (or Net 1) in the current study, while the second neural network used to forecast day-ahead spike prices in this work is called Network 2 (or Net 2).

The present paper is organized as follows. Section 2 describes the proposed method for spike price forecasting. Results and discussion are presented in Sect. 3. Section 4 concludes the paper.

2 Proposed Method for Spike Price Forecasting

2.1 Electricity Price Spikes

Spikes in the electricity market may be considered as random events. Many studies in the past have shown encouraging results on the spike forecasting and discussed the reasons for occurrence of spikes [2, 8–14]. Mainly spikes occur if the available supply is less than demand or if the reserve margin is very low. There are many short-term factors, such as breakdown of generators operating at low cost, transmission line constraints, generation capacity constraints, and weather conditions like temperature, humidity and dew point temperature, affecting the occurrence of spikes. There are also long term factors, such as hikes in gas and oil prices, shutting down of generators due to ageing, government policies, inflation rates, and economic growth.

Electricity market spikes may be divided into three categories: high spikes (if the prices are much higher than the average prices), negative spikes (if the prices are below zero), and jump spikes (if there is a significant change in the prices at time '$t + 1$' from price at time 't'). In the Ontario electricity market, if the demand is less than the supply electricity prices are negative and buyers are paid for energy consumption. Spikes may occur for several hours but normally not for more than a day.

In this study, high spike prices are analyzed and forecasted day-ahead over a day for the Ontario electricity market. As shown in Table 1, the number of electricity price spike hours in Ontario is increasing every year. Hence, to fulfil the demand during these spike hours new generation facilities may be needed. These facilities are operative only for a few hours for a few days in a year, but have a significant impact on increases in electricity prices. In the Ontario electricity market, historical prices, demand, temperature, dew point temperature and relative humidity data are selected as important features for forecasting price spikes. These features are available for public access on the Independent Electricity System Operator (IESO) website at ieso.ca.

Table 1. Number of spike hours and spike days from 2009 to 2014.

Year	Number of spike hours	Number of spike days
2009	21	12
2010	44	25
2011	61	36
2012	58	33
2013	73	67
2014	122	95

The historical price data are obtained for the Ontario wholesale electricity market for 2011 and the mean 'μ' and standard deviation 'σ' are calculated. Then the price spike threshold for 2012 is calculated as $\mu + 2\sigma$ [2, 8]. The threshold level is computed as $71.26/MWh for 2012 and prices above this threshold are considered spikes. When prices are forecasted to be above this threshold by the neural network presented in Sandhu *et al.* [16], the second neural network is utilized to predict the spike prices. The threshold for 2012 is calculated from the mean and standard deviation of the prices in 2011. Similarly, the threshold for 2013 can be computed from the mean and standard deviation of the prices in 2012.

2.2 Flow Chart of the Proposed Method

A hybrid neural network-based method is proposed in the present study to forecast the electricity price spikes over a day. In the first step, a neural network (called Network 1 or Net 1) along with the data mining techniques at the pre-processing step presented by Sandhu *et al.* [16] is used to forecast the day ahead prices for a forecasting day. The mean absolute percentage errors (MAPEs) are often large at spike hours. In the next step, as shown in Fig. 1, a classifier is employed to classify the forecasted prices to be below, above or equal to the threshold price. The prices above or equal to the threshold are considered as spike prices. In the third step, in order to improve the accuracy of forecasting, a second neural network (called Network 2 or Net 2), as shown in Fig. 2, is used to forecast the spike prices and the overall forecasting is achieved by combining the results of two networks. Network 2 is trained with discrete values over the spike hours from the same year prior to the forecasting day and from the previous two years

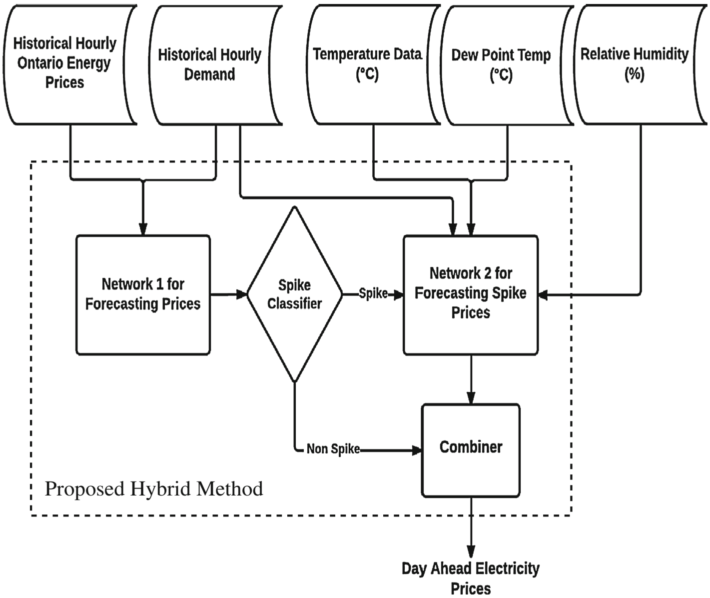

Fig. 1. Flow diagram of day-ahead electricity price spike forecasting.

with price, demand, temperature, dew point temperature, and relative humidity data. Dew point temperature is the absolute measure of moisture in the air and at the dew point temperature water vapor will condense. On the other hand, the relative humidity gives an expression for air saturation at a given temperature. As an example, to forecast the spikes for January 3, 2012, spike hours for January 2 and January 1, 2012 from the same year are identified and spike hours over all 365 days in 2011 and 2010 are identified as the spike hours from the previous two years. Training dataset, to train Net 2, consists of these identified spike hours. Spikes do not occur continuously, therefore, the training dataset for Net 2 consists of these discrete hours. Hence, prices above the threshold level, as forecasted by Network 1, are re-forecasted by Network 2 trained

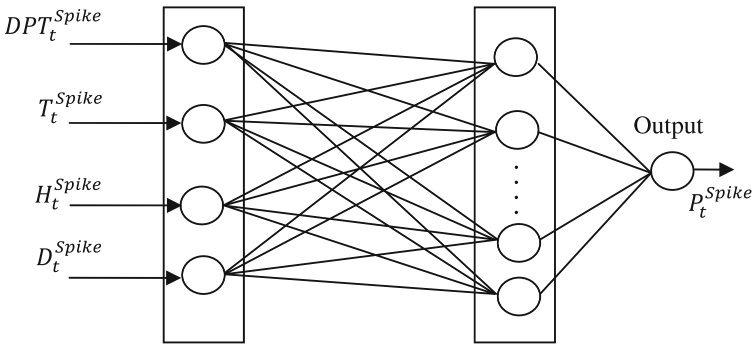

Fig. 2. Proposed network 2 for spike price forecasting

Table 2. Forecasting day-ahead electricity prices and spikes using neural networks.

Hour	January 3, 2012			June 20, 2012			June 28, 2012		
	Actual	Net 1	Net 2	Actual	Net 1	Net 2	Actual	Net 1	Net 2
1	28.34	30.25		20.28	22.89		14.17	14.41	
2	27.69	30.14		21.64	23.28		16.64	15.89	
3	25.31	28.79		18.59	20.16		12.47	13.34	
4	25.22	28.65		19.5	20.48		12.65	13.43	
5	25.88	28.72		16.4	18.24		13.06	12.78	
6	26.66	28.97		20.34	19.63		4.38	4	
7	31.16	33.59		27.24	24.87		15.8	15.68	
8	34.77	36.87		31.15	28.55		21.06	20	
9	35.89	37.29		47.59	41.98		22.71	21.9	
10	33.82	36.37		56.88	52.86		28.24	25.2	
11	32.96	36.16		38.29	45.19		31.31	31.9	
12	29.05	33.29		50.51	49.55		29.16	31.73	
13	31.62	34.57		88.81	76.49	82.59	31.5	31.42	
14	31.48	34.46		66.28	70.7		30.7	31.04	
15	47.13	38.97		108.24	88.92	99.28	38.82	37.44	
16	44.83	37.86		44.68	68.49		93.76	78.79	84.12
17	58.15	45.78		95.06	81.59	86.87	100.1	91.36	96.82
18	115.2	79.46	92.76	95.79	86.79	91.36	71.86	76.77	73.23
19	91.28	76.89	86.79	97.89	89.26	93.08	45.37	42.19	
20	135.3	94.79	119.4	62.7	79.83	72.89	44.38	46.21	
21	124.7	93.23	115.4	46.38	58.22		47.15	45.6	
22	41.33	78.49	82.37	28.95	38.76		56.56	53.58	
23	32.09	70.12		26.06	32.11		31.39	36.06	
24	29.16	62.79		24.13	27.14		21.7	20.42	

(*Continued*)

Table 2. (*Continued*)

Hour	July 6, 2012			July 17, 2012			July 18, 2012		
	Actual	Net 1	Net 2	Actual	Net 1	Net 2	Actual	Net 1	Net 2
1	21.13	23.59		28.44	26.33		32.93	30.36	
2	20.92	22.89		25.88	24.26		27.42	28.13	
3	19.87	22.09		24.99	24.11		26.32	27.04	
4	17.43	19.38		23.79	24.06		25.67	26.11	
5	16.55	19.24		23.94	24.08		25.94	26.15	
6	18.93	20.63		24.18	24.12		25.47	25.83	
7	24.39	21.94		25.33	24.49		26.03	25.94	
8	25.16	23.88		28.32	26.79		27.46	26.97	
9	30.47	27.49		32.39	29.86		27.34	26.94	
10	59.01	42.68		65.05	48.22		31.9	31.18	
11	107.06	75.21	87.27	87.79	67.59		35.54	34.22	
12	77.16	79.96	80.76	120.4	79.46	90.27	41.12	39.25	
13	119.04	97.26	112.76	138.3	86.33	115.5	71.91	66.43	
14	96.24	89.57	101.25	103.3	75.22	99.56	32.05	34.21	
15	96.33	90.29	99.87	105.1	76.43	101.7	43.46	41.83	
16	94.72	89.64	98.59	144.3	89.76	129.4	89.15	73.58	74.82
17	93.17	89.88	97.92	147.7	95.78	135.8	97.32	79.85	85.24
18	64.23	80.29	75.29	149.2	103.7	139.5	30.31	32.59	
19	43.37	69.58		148.2	103.5	140.8	29.2	31.08	
20	88.85	82.59	86.24	96.49	90.78	112.7	31.66	31.88	
21	86.84	82.05	85.46	69.71	78.65	82.49	30.82	31.09	
22	53.9	78.91	62.34	39.28	68.46		25.26	27.16	
23	53.17	62.15		41.45	68.78		22.88	23.54	
24	22.36	32.65		35.51	54.12		20.74	21.82	

(*Continued*)

Table 2. (*Continued*)

Hour	4-Aug-12			24-Aug-12		
	Actual	Net 1	Net 2	Actual	Net 1	Net 2
1	27.44	26.49		25	24.85	
2	26.45	26.13		21.71	22.36	
3	27.47	26.89		18.64	18.78	
4	27.32	26.88		13.79	14.91	
5	25.37	26.03		19.17	19.89	
6	24.32	25.79		19.35	17.83	
7	25.77	26.11		18.3	19.22	
8	23.79	25.31		20.89	20.65	
9	24.81	25.46		22.67	22.32	
10	45.76	38.47		23.4	23.28	
11	58.58	42.19		26.88	25.79	
12	54.06	41.27		25.31	25.98	
13	84.14	67.49		31.56	29.65	
14	92.38	76.49	85.46	31.76	31.75	
15	100.75	85.64	92.37	77.52	54.27	
16	162.07	134.25	149.66	135.9	118.6	129.3
17	157.31	130.46	148.55	97.72	121.8	106.4
18	94.57	104.79	97.65	28.91	38.53	
19	109.79	118.34	112.43	28.47	28.6	
20	151.33	142.24	148.79	25.73	26.76	
21	49.97	94.37	79.58	22.65	23.79	
22	25.89	76.28	59.48	26.43	24.96	
23	23.77	69.42		20.62	23	
24	23.33	62.72		22.36	22.14	

with discrete values at spike hours. Spike prices forecasted by Network 2 are then combined with the previously forecasted prices of Network 1 to achieve the complete day-ahead electricity price forecasting to improve accuracy.

Network 2, as shown in Fig. 2 is used to forecast spike prices at '*t*' hour. Input features applied to Network 2 are $DPT_t^{Spike}, T_t^{Spike}, H_t^{Spike}$ and D_t^{Spike} as dew point temperature, temperature, relative humidity and demand at spike hour '*t*', respectively. The output of Network 2 is the forecasted spike hour price P_t^{Spike} at hour '*t*'. Hidden neurons are increased from seven neurons in Network 1 to twelve neurons in Network

2 because of the increase in the number of input features. The other training parameters of Network 2 are kept the same as in Network 1.

3 Results and Discussion

The proposed spike price forecasting method uses the historical data available to the public from the Ontario electricity market at ieso.ca. A detail description of the Ontario electricity market is available in Zareipour *et al*. [4]. Previous studies on forecasting prices for the Ontario electricity market are mostly focused on normal price forecasting [17–20]. The proposed method presented in Sect. 2 is utilized to forecast spike prices for the Ontario electricity market. Eight spike days in 2012 are selected for numerical experiments. The forecasting results are given in Table 2.

As discussed in Sect. 2, the neural network developed by Sandhu *et al.* [16] is first used to forecast electricity prices during these selected days. The results are given under the column entitled “Net 1”. The prices above the 2012 threshold of $71.26/MWh are highlighted in Table 2. As can be seen, the spike hours, the forecasted prices deviate from the actual prices significantly. Next step, Network 2 is used to forecast prices over the spike hours for the selected days. These forecasting results are given in the column entitled “Net 2”. The proposed method combines the results from Network 1 and Network 2 to form the complete day-ahead price forecasting for each day. The MAPEs are calculated for these selected days in 2012, as shown in Table 3. As can be seen, the MAPEs are significantly reduced from Network 1 to the proposed method. An overall average MAPE value of 11.76 % for eight selected days in 2012 is achieved.

Table 3. Comparison of methods in terms of MAPE.

Day	Network 1	Hybrid neural network-based method
January 3, 2012	26	20.2
June 20, 2012	14.8	11.6
June 28, 2012	6.87	5.15
July 6, 2012	15.6	11.2
July 17, 2012	27.9	14.7
July 18, 2012	6.9	6.1
August 4, 2012	24.1	17.2
August 24, 2012	11.02	7.96
Average MAPE	**18.57**	**11.76**

Forecasting for normal prices and spike prices is demonstrated for eight different days from the summer and winter seasons in 2012. Day-ahead hourly forecasting for January 3, 2012 is shown in Fig. 3 and the overall MAPE value for the day is decreased from 26 % to 20.2 %. The forecasting results are obtained with two neural networks trained for normal and spike price forecasting. As can be seen, at spike hours, the results from the proposed hybrid method follow the actual prices much closer.

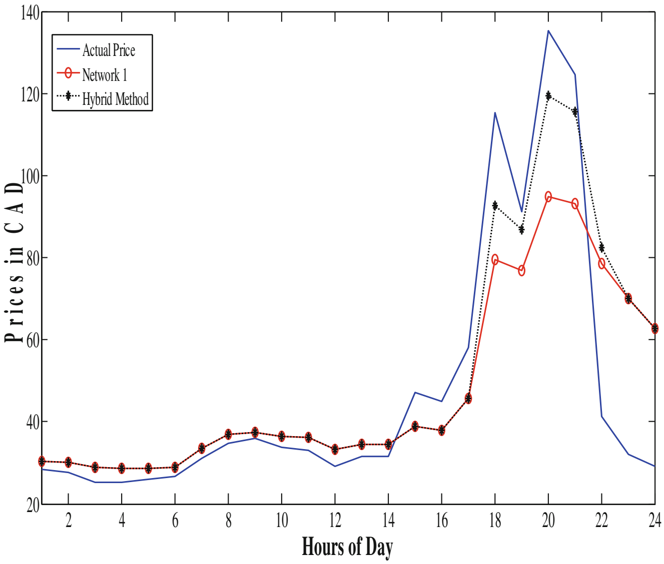

Fig. 3. Forecasting of prices for January 3, 2012.

Figure 4 illustrates normal and spike price forecasting for a summer day, July 17, in 2012, over the period of 24 h, with an overall improvement of MAPE from 27.9 % to 14.7 %. In a similar manner, hourly forecasted normal and spike prices have been obtained over all the selected days and the results are shown in Table 3.

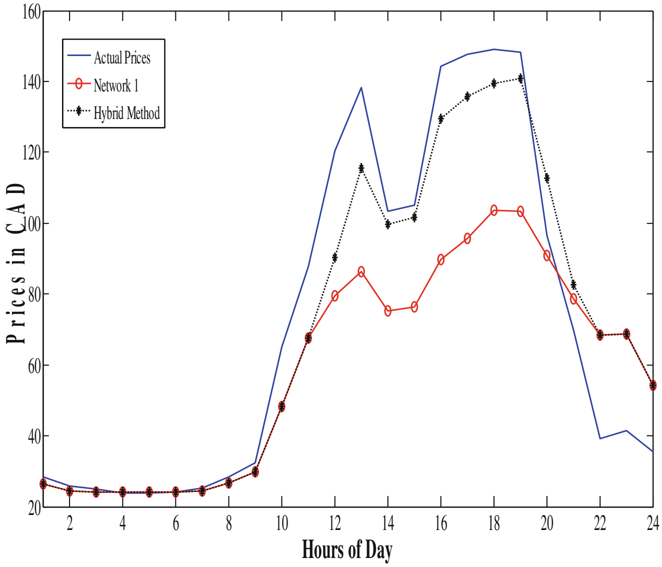

Fig. 4. Forecasting of prices for July 17, 2012.

It is observed that the first neural network, developed in a previous study by Sandhu *et al.* [16], is capable of forecasting day-ahead electricity prices with high accuracy for the low and medium price ranges. However, forecasting errors increase significantly as prices pass the threshold level defined by $\mu + 2\sigma$. These prices are considered as spikes and the second neural network, trained over the spike hours prior to the forecasting day in the same year and from the previous two years, is able to forecast spike prices. The proposed hybrid neural network-based method, combining results from the first and second neural networks, improves the overall forecasting accuracy.

4 Conclusion

A new approach for forecasting hourly normal and spike prices has been presented for the Ontario wholesale electricity market. Two feed forward neural networks trained differently are used along with a spike classifier to forecast day-ahead electricity prices. Forecasting experiments are carried out for eight different days, from different seasons, in 2012. Numerical experimental results show that the first neural network is able to predict electricity prices with high accuracy for the low and medium price ranges. However, with jumps in price, the forecasted prices deviate from the actual prices significantly and accuracy decreases. The prices above the pre-defined threshold level are known as spikes. The second neural network trained with historical spike hours from the same year and from the previous two years reduces forecasting errors over the spike hours. Experiments show that the overall MAPE is improved from 18.57 % to 11.76 %, an improvement of 36.7 % by the proposed hybrid neural network-based method. It is also observed from the 2012 data from the Ontario wholesale electricity market that spikes occurred when the demand was high and most of the spikes occurred during the summer season.

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