Artificial Neural Network-based Electricity Price Forecasting for Smart Grid Deployment

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***Abstract*—A deregulated electricity market is one of the keystones of up-and-coming smart grid deployments. In such a market, forecasting electricity prices is essential to helping stakeholders with the decision making process. Electricity price forecasting is an inherently difficult problem due to its special characteristics of dynamicity and nonstationarity. In our research, we use an Artificial Neural Network (ANN) model on carefully crafted input features for forecasting hourly electricity prices for the next 24 hours. The input features are selected from a pool of features derived from information such as past electricity price data, weather data, and calendar data. A wrapper method for feature selection is used in which the ANN model is continuously trained and updated in order to select the best feature set. The performance of the proposed method is evaluated and compared with the published results of the state-of-the-art Pattern Sequence-based Forecasting (PSF) method on the same data sets and our method is observed to provide superior results.**

***Index Terms*—Price forecasting, feature selection, artificial neural network**

I. Introduction

The pricing of most goods and services are based on supply and demand, and electricity is no exception. In a smart grid deployment, by liberalizing the pricing in the electricity market, suppliers will be able to reduce the wastage of excess electricity when demand is low, and ensure sufficient supply when demand is high. This scenario exists since the usage of electricity will depend on the price per unit at a particular time of day when consumers (usually electricity retailers) have access to an electricity pool where they decide what time to buy electricity from the pool (usually the whole sale market). Thus every retailer is very concerned about the price in the coming hours, days or may be in the coming month.

The problem of electricity price forecasting is related yet distinct from that of electricity load forecasting. Although the demand (load) and the price are correlated, their relation is non-linear. The load is influenced by the factors such as non-storability of electricity, consumers' behavioral patterns, and seasonal changes in demand. The price, on the other hand, is affected by those aforesaid factors as well as additional aspects such as financial regulations, competitors' pricing, dynamic market factors, and various other macro- and micro economic conditions. As a result, the price of electricity is a lot more volatile than the electricity load. Interestingly, when dynamic pricing strategies are introduced, prices become even more volatile, where the daily average price changes by up to 50% while other commodities may exhibits about 5% change [11].

Load forecasting has progressed to a point where the load can be predicted with up to 98% of accuracy in some cases [6]. However, current state-of-the-art techniques in price forecasting are at most about 95% accurate [14]. Thus, a more accurate price forecasting system is necessary since many retailers and their businesses depend on the prices of electricity.

Our objective is to build an accurate electricity price forecasting model for generating hour-ahead price forecasting. This price forecasting is important for the transmission company to schedule short-term generator outages, design load response programs as well as bid into the market strategically and manage its assets optimally. When accurate price forecasting system is available, large consumers can stem their electricity usage plan strategically to maximize their utility.

Many papers have been published in the area of price forecasting using Artificial Neural Network (ANN) for price forecasting. Here, our main contribution lies on extracting the best features from a pool of features and training the ANN with these features in order to create a real-time forecasting model. As mentioned in [10], lagged prices are generally used in price forecasting since its high autocorrelation with electricity market prices. However, in a real-time setup, apart from the system load and price during the previous hour, no other features are available, thus restricting us to features from the available pool.

Even though a lot of research has been performed on electricity price forecasting, none of the experiments provides a sufficiently accurate model with less than 5% mean absolute prediction error (MAPE) value. This indicates that there is still room for improvement. It should be noted that some models proposed performed well in certain electricity markets whereas the same model shows very bad results in a different market. A simple general model which can forecast in many markets with a good level of accuracy is our aim.

Due to the importance of accurate price forecasting in volatile electricity markets, a number of approaches have been presented in the literature. These approaches range from traditional time series analysis to machine learning techniques for forecasting future prices. ARIMA [11] and GARCH [9] models are examples of traditional methods, while artificial neural networks (ANN) [15], Hidden Markov Models [16], fuzzy inferred neural networks [5] and support vector regression are examples of machine learning techniques.

In [14], Martínez-Álvarez *et. al* presented a method which was based on pattern sequence similarity. In this approach, a clustering technique was first used on the data before application of the Pattern Sequence-based Forecasting (PSF) algorithm to produce one step ahead forecasts of the electricity prices. In the experiment, k-means clustering was used to cluster the training data. The training is performed using data collected from 3 different electricity markets, namely New York (NYISO) [2], Australia (ANEM) [1] and Spain (OMEL) [3], for the years 2004–2005, while testing is carried out for using data from 2006. The authors perform a detailed analysis

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using these three different datasets, and compared their results to those obtained using other methods. As this work is quite recent and the three datasets used are publicly available, we use the results described in this paper as benchmarks in order to evaluate our proposed method.

II. The Proposed Method

Feature creation and selection is the first step in classification or regression (i.e., forecasting in our context). It is a widely used process in machine learning and involves either the creation of new features or the selection of an optimal subset from a pool of existing features. The selected subset will contain key features which contribute to the accuracy of the forecasts and also help reduce over-fitting of the model. Our approach towards creation and selection of features as well as training and updating the ANN model is shown in Figure 1.

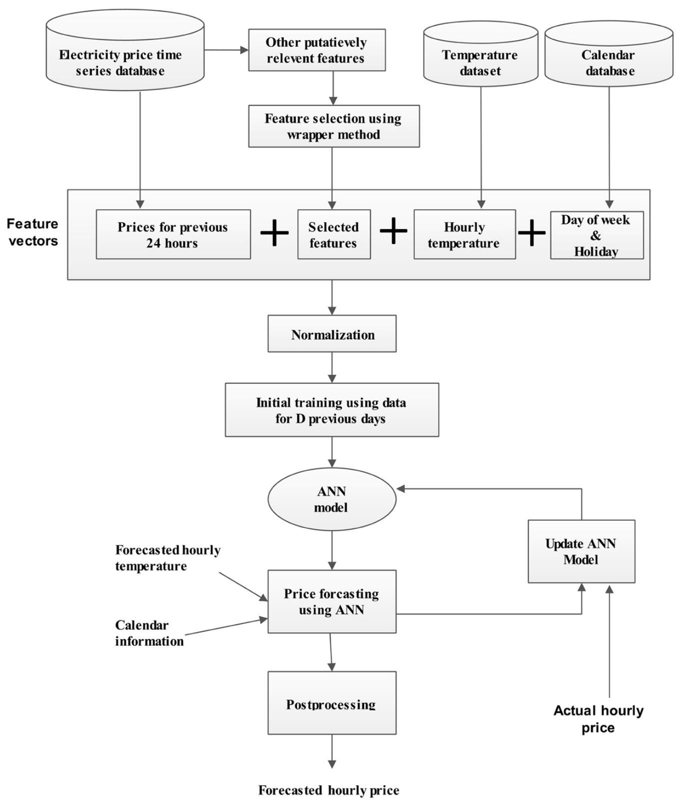

Fig. 1. Overview of the proposed price forecasting scheme.

A. Data Preprocessing

1) Feature Extraction: The electricity market data comes in the form of a time series, i.e. as (time, value) pairs, and does not provide any specific features for use with ANN. Thus we have to create features from the available past data to be used as inputs to the ANN. We analyzed the input data using a similar approach to the method in [6] and create about 20 features from the available electricity market data. Hourly data is extracted for 24-hour windows, yielding 24 features with which we seek to forecast the electricity price for the following hour. The best features that give short term trend in the price market are past 24 hour data which has been verified in [7]. But this data does not capture the seasonal behaviors and long term trends.

In price forecasting, it is important to take into account both short and long term trends and also seasonal patterns. Sudden changes in the price might be caused by seasonal behaviors and other factors. In order to capture this behavior we create putatively relevant features based on historical data which lasts for longer period. We create features such as last year same day same hour data, last year same day same hour price fluctuation, last week same day same hour price,last week same hour price fluctuation etc.

Though we create many features from historical data, we cannot use all generated features since training accuracy depends on the number of features. To achieve higher forecasting accuracy, over-fitting and over training of ANN should be avoided. In order to select the best features we use feature selection techniques as described in the next section.

2) Feature Selection: Feature selection is a very important step towards building a robust forecasting model. In this paper, the *wrapper* method [12] in WEKA was used for subset selection from a large pool of features. Wrappers implement search algorithms for finding the subset of features in feature space and evaluate the subset using the model or learning algorithm. Each feature subset is evaluated based on the estimated accuracy obtained using the learning algorithm. Estimation of accuracy is done using cross validation (for the results presented in this paper 10-fold cross validation was used). Wrappers methods are most widely used in the context of supervised learning problems where labels are available. It can also be used for unsupervised learning problems where some other target or objective function which results in better clusters is used instead of classification accuracy.

After creating around 20 features that capture long term trends and past 24 hour data as 24 features we perform feature selection to find the best set of features. Due to large pool of features we divide the feature set into two as 24 hourly features in one pool and rest of the features in another pool. As described in [7], past 24 hourly price features capture the current short term trend and selecting only a subset of these features will diminish the accuracy of the model. Thus, we used this verified approach and select all the 24 features to be used in our ANN model.

In selecting the best feature set, the wrapper method was applied to all features except those associated with the past 24 hours. Technically, this training accuracy may be less than the best possible accuracy since we did not incorporate the past 24 hour data. Once we apply all the data, including the past 24 hour data, to the wrapper, it take a much longer time since the wrapper method is computationally very expensive. Due to the verified importance of the past 24 hour data, we choose to drop it from our feature selection using wrapper and select the best features from the remaining ones with the wrapper using 10 fold cross validation. As an example, the final feature set obtained for New York (NYISO) dataset after feature selection process is shown is Figure 2.

3) Incorporating Other Features: Features generated using historical prices already gave good forecasting results, but it is possible to improve the accuracy by considering other features that are not directly associated with price data. Other parameters that could plausibly affect the load or price in the market were considered; based on [4], we further decided

Prices for previous 24 hours	Previous year same hour's price	Previous year same day same hour's price	Previous year same day's average price	Previous week same hour's price	Previous hour's price increase/decrease	Previous year same day same hour's price increase/decrease	Temper -ature	Day of week	Holiday

Selected features

Fig. 2. Features used for training and testing of New York (NYISO) dataset.

to incorporate the temperature, day of the week and the occurrence of holidays into the generated feature set.

In order to forecast the price in the following hour, we would need the temperature in that particular hour. However, as this is not available in real time, we used the predicted temperature that is provided by a weather forecasting service. For training and testing purposes historical data was used but for real time use we can use a service such as *wounderground.com* to get the forecasted temperature value. For the holiday data we use predefined holidays in the tested region and directly bound them with the existing data.

The neural network model was trained and tested without temperature and holiday features together with other selected features; next the temperature and holiday features were incorporated and the model was trained and tested. It was seen that the use of temperature and calendar-based features improved the accuracy of the system. Hence, these features were used in the final model. Some may argue that oil and gas prices and many other factors also affect the pricing. However, it is not easy to have accurate predictions of oil and gas prices for incorporation into our model.

4) Normalization: Normalization is compulsory in ANN where the input data is different from each other and ranging in different measurements and scales. In our approach we defined various input data that has different scales, thus we normalize the data to achieve a consistent form. We use *mapminmax* function available in Matlab to normalize our input data. Mapminmax returns a normalized matrix by normalizing the each row to the range of provides min and max values. In our method we normalize the data into the range $(-1.0, 1.0)$.

B. Constructing ANN Model

Many models of ANN has been proposed for classification and regression (forecasting) problems in machine learning. Out of all the models, hte multilayer perceptron is the best known and most widely used. Typically, a feedforward ANN contains unit arranged in 3 layers, input, hidden and output. Each layer contains a number of units which might contain shared information but which are not connected to each other. In our ANN model we selects 3 layer network with 10 nodes in the hidden layer.

To perform forecasting using a neural network, two basic steps are required: training, and learning. We assume that the training set containing historical data along with desired output is available. In the learning step the neural network learns to reconstruct the input-output mapping by updating the weight of inputs and biases at the end of each iteration. Backpropagation is the most common learning algorithm, in which at the end of each iteration output error is propagated back to input adjusting the weight and biases. To overcome the slow convergence rate of the backpropagation algorithm, two parameters, learning rate and momentum can be adjusted. In this paper, we implemented the Levenberg-Marquardt algorithm for training because of its rapid convergence. Matlab's built-in Neural Network toolbox was used for training, learning and forecasting of electricity prices using ANN.

III. Experimental Results

We use our method to forecast electricity prices in three different electricity markets as New York (NYISO) [2], Australia (ANEM) [1], and Spain (OMEL) [3] markets. We select these market as mentioned in [14], due to the vast research carried out in the area based on these data markets. From NYISO we selected "Capita" as the reference area to benchmark with previous experiments. The NYISO electricity market is deregulated and the system provides hour- and day-ahead forecasted electricity prices. The Australian Electricity Industry deregulated from 1995 and currently Australian National Electricity Market (ANEM) conducts market clearing in every half hour. We select Queensland area as the reference since we benchmark the results with above mentioned research. For the Spanish market we use the same data that used by [14] in their experiment.

A. Experiment I: 2004–2006

Results are presented for the NYISO, ANEM, and OMEL datasets. For 2004–2006, data for March 2004–March 2006 was used for training while data for April 2006–December 2006 was used for testing.

1) NYISO Dataset: Table I shows mean error rate (MER), mean absolute error (MAE), and mean absolute percentage error (MAPE) obtained for all datasets used for validation of the model for year 2006. In spite of using less training data in Table I, we can see that the result obtained for the New York data has MER of 4.13 % with S.D. (standard deviation) of 1.02, MAE of 2.37 with S.D. of 0.52 and MAPE of 4.18% with S.D. of 0.74. The worst month was December where MER is 5.90%, MAE is $3.18/MWHr and MAPE is 5.75.

The upper half of Figure 3 depicts the worst and the best forecasted days in 2006 testing dataset. It is visible that in NYISO market our model forecasts the prices with higher accuracy.

2) ANEM Dataset: The Australian electricity market is highly volatile with a large number of unexpected abnormalities and outliers. There were large fluctuations in prices, where the with highest price was $9739/MWHr in the month of January 2006 and the lowest price was $7.81/MWHr, which was in the 1st day of February 2004. As a result of these large fluctuations and outliers, the price forecasts for this market had higher errors. From Table I, we can see that performance of our approach for Australian market has 9.41% of MER with S.D. of 3.75 and MAE of $3.14/MWHr with S.D. of 1.25 and MAPE of 8.17% with S.D. 2.78. Though the result of our approach has higher error percentage, still its performance is better than the other researches performed on this dataset. MER of our approach for this market is slightly

TABLE I
MER, MAE AND MAPE IN NYISO, ANEM AND OMEL MARKETS FOR IN YEAR 2006 (EXPERIMENT I) AND THEIR COMPARISONS WITH PSF RESULTS.

	NYISO					ANEM					OMEL				
	MER (%)		MAE ($/MWHr)		MAPE (%)	MER (%)		MAE ($/MWHr)		MAPE (%)	MER (%)		MAE ($/MWHr)		MAPE (%)
	Ours	PSF	Ours	PSF	Ours	Ours	PSF	Ours	PSF	Ours	Ours	PSF	Ours	PSF	Ours
Jan		4.45		2.25		13.96	5.8	4.66	1.51	13.34	6.00	7.26	0.40	0.53	5.07
Feb		5.53		3.02		7.26	8.59	2.42	5.15	7.19	5.25	4.93	0.35	0.36	3.66
Mar		6.30		3.97		4.59	7.84	1.53	1.73	4.79	5.28	5.88	0.35	0.43	6.19
Apr	3.99	4.94	2.34	3.51	4.02	5.60	9.92	1.87	1.98	5.82	5.90	3.62	0.39	0.28	5.73
May	2.94	7.59	1.72	4.63	3.23	10.07	12.85	3.36	3.21	9.59	6.00	8.11	0.40	0.64	6.11
Jun	3.65	3.34	2.14	2.31	3.83	11.00	22.04	3.67	6.81	7.85	5.14	3.76	0.34	0.29	5.27
Jul	4.09	3.93	2.40	2.28	3.95	17.97	17.11	5.99	8.16	13.84	4.59	4.30	0.30	0.33	4.55
Aug	4.82	5.37	2.82	3.49	3.96	11.28	11.71	3.76	3.32	7.55	5.17	5.37	0.34	0.42	5.57
Sep	2.86	6.24	1.68	4.49	3.60	8.77	8.23	2.93	2.34	7.03	5.66	6.41	0.37	0.50	5.42
Oct	3.36	7.43	1.97	4.23	4.09	5.70	7.66	1.90	1.92	5.40	6.08	7.89	0.40	0.58	6.64
Nov	5.53	5.19	3.05	3.53	5.17	10.59	6.76	3.53	2.09	9.25	3.94	8.30	0.26	0.64	7.25
Dec	5.90	6.04	3.18	3.08	5.75	6.12	6.42	2.04	1.41	6.35	5.04	8.02	0.33	0.59	7.61
Mean	4.13	5.53	2.37	3.40	4.18	9.41	10.41	3.14	3.30	8.17	5.34	6.15	0.35	0.47	5.76
S.D.	1.02	1.94	0.52	0.39	0.74	3.75	4.66	1.25	2.13	2.78	0.61	1.68	0.04	0.13	1.06

Note: January–March results are missing in the case of NYISO because the corresponding training data required by our method is not available. Comparison with PSF [14] is not reported for MAPE because PSF did not employ MAPE as its performance indicator.

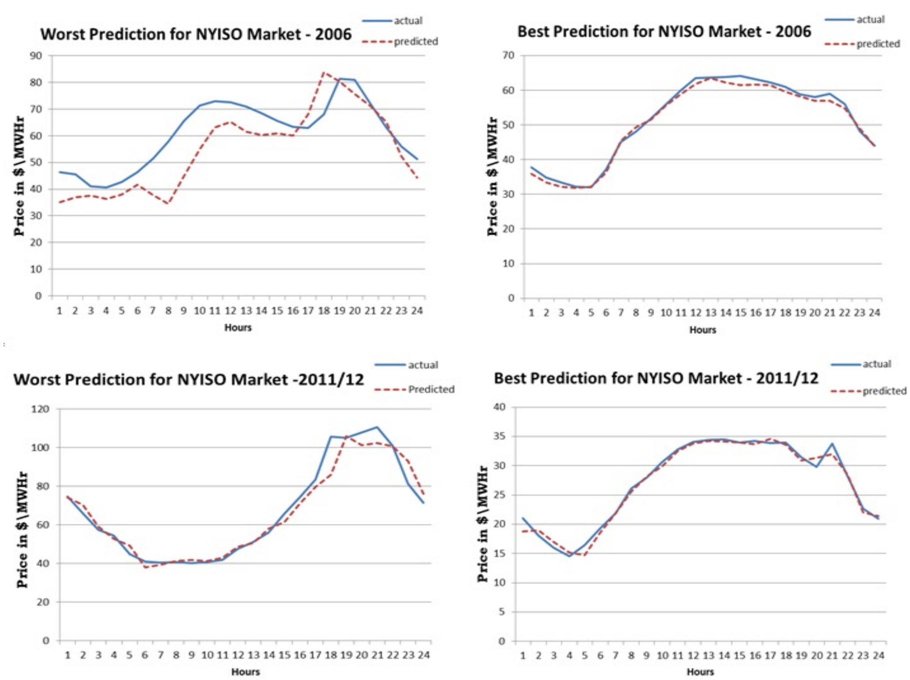

Fig. 3. The worst and the best forecasted days in NYISO market in year 2006 (Experiment I) and years 2011–2012 (Experiment II).

better than the previous research, whereas there is greater accuracy achievement in the MAE.

The worst performance was in the months of January, July and August with worst performance of 17.97% MER in July and the best performance of 4.59% MER was obtained in the month of March. The best MAPE of 5.40% was obtained for the month of October and the worst MAPE of 13.84% in the month of July. The best forecasted day and the worst forecasted day for year 2006 is depicted in the upper half of Figure 4. Though this accuracy is less than that of NYISO market data, results revealed that our forecasting accuracy is higher than that of its competitor method, namely PSF.

3) OMEL Dataset: For Spanish electricity market we collected data from 2004-2006. Data from2004 and 2005 was used for training and data for 2006 was used to test the resulting model. The results obtained from the Spanish market are shown in Table I, we can see that the average MER for year 2006 is 5.34% with S.D. of 0.61, which shows that the monthly error are around the average error. MAE for the Spanish data is $0.35/MWHr with the S.D. of 0.04 and MAPE of 5.76% with S.D. of 1.06. MAE for Spanish data is very low compared to other market because of its relatively very low average energy prices compared to others. The worst and the best forecasted days for year 2006 is depicted in Figure 5.

4) Comparison with PSF: To validate our method, we compared our results with those obtained in other studies found in the literature. We select Pattern Sequence-based Forecasting (PSF) method as our benchmark for analysis since in their experiment, it proves that results are above aforementioned other concurrent works. Thus without comparing with a lot more techniques, we perform a comparison with PSF to validate our results. In the PSF model they compare their

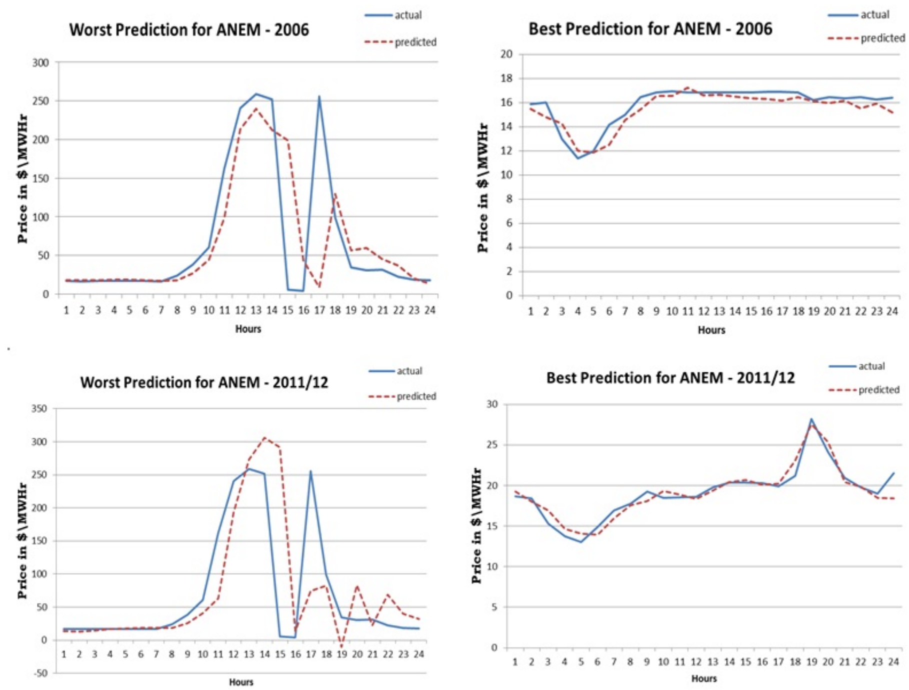

Fig. 4. The worst and the best forecasted days in ANEM market in year 2006 (Experiment I) and years 2011–12 (Experiment II).

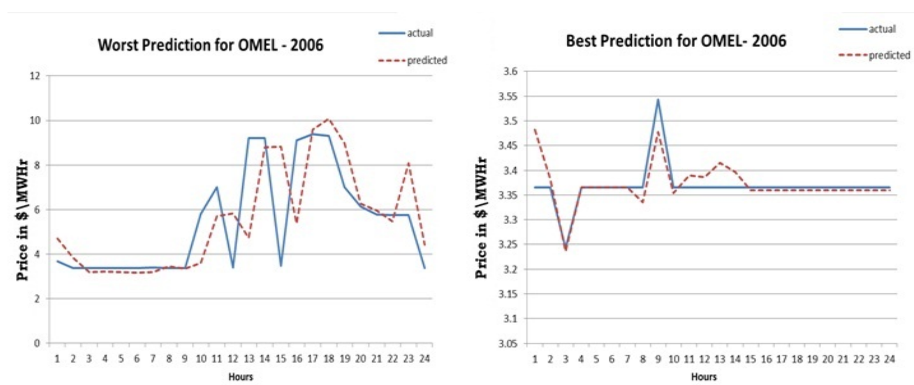

Fig. 5. The worst and the best forecasted days in OMEL market in year 2006 (Experiment I).

results with ARIMA model, naive, ANN, WNN (Weighted Nearest Neighbor) [13], STR [8] and other mixed models. As PSF paper performs testing on year 2006 data from all three markets we perform the testing on same data and results depicted in Table I. As shown in the table, we can argue that our method forecasts with 1.4% MER improved accuracy in NYISO market for year 2006. It has a slight improvement of 1% MER over the ANEM market and 0.81% MER improvement in OMEL market for year 2006 data.

For numerical analysis, MAE measure also proved high accuracy with \$1.03, \$0.16, \$0.12 per MWHr improvements for NYISO, ANEM and OMEL markets respectively. With our model, it provides better forecasting as indicate by MER factor, also S.D. in MER for NYISO is also less with compared to PSF model as it indicates 1.02% with our model and 1.94% with PSF model. For MAE value the S.D. is a little higher than PSF model but our model provides better forecasting having a less MAE value compared to PSF model. For the ANEM market which has significant abnormalities in the dataset, our model's MAE had a S.D. of 1.25 whereas in the PSF model the S.D. is 2.13, which also indicates higher forecasting accuracy since our MAE value is less than that for PSF model. For MER in ANEM market, our model has a less S.D. 3.75 with compared to PSF which is 4.66. Forecasting for OMEL market also provides better accuracy as indicated by the relevant S.D. values indicated in Table I.

For NYISO market we test our model from April 2006 to December 2006 due to unavailability of data in first 3 months in year 2004 to train with our model. But we can argue that our model provides a less MER with very less S.D. affirming that for this months also we can get better results.

B. *Experiment II: 2008–2012*

To further verify our method's good performance, we ran a second experiment using data which is more recent than that used in Experiment I. For this second experiment, the

TABLE II
MER, MAE, AND MAPE PERFORMANCE INDICATORS FOR NYISO AND ANEM MARKETS FOR YEARS 2011–2012 (EXPERIMENT II).

	NYISO			ANEM		
	MER (%)	MAE ($/MWHr)	MAPE (%)	MER (%)	MAE ($/MWHr)	MAPE (%)
Jun	4.27	2.01	4.31	4.60	1.28	4.62
Jul	4.66	2.97	4.72	7.46	2.07	6.94
Aug	3.54	1.56	3.51	5.06	1.41	4.44
Sep	3.86	1.47	3.76	4.43	1.23	4.25
Oct	3.55	1.33	3.48	4.64	1.29	4.57
Nov	3.61	1.30	3.62	7.33	2.03	6.10
Dec	4.01	1.44	4.16	5.01	1.39	4.72
Jan	4.92	2.32	5.14	13.88	3.30	9.09
Feb	3.70	1.20	3.81	15.28	5.63	13.53
Mar	4.83	1.31	4.86	14.01	4.44	11.89
Apr	4.18	1.06	4.09	5.68	1.58	5.21
May	3.45	0.88	3.27	3.95	1.10	4.07
Mean	4.05	1.57	4.06	7.61	2.23	6.62
S.D.	0.50	0.56	0.57	4.06	1.40	3.06

NYISO and ANEM markets were again used; data from June 2008–May 2011 was used as the training set and June 2011–May 2012 data as the test set. (Note: OMEL dataset is not available for 2008–2012.) It is observed that the results of this Experiment II are even slightly better than those in Experiment I.

1) NYISO Dataset: From Table II, we can see that the performance of our model is as good as with the data from 2006 though the 2011-2012 data contains many spikes and outliers. For 2011–2012 data, we obtain the MER of 4.05% with S.D. of 0.5, MAE of $1.57/MWHr with S.D. 0.56 and MAPE 4.06% with S.D. of 0.57. we can see that there is a slight improvement in the forecasting result for the latest data with a reduction in MAE by $0.8/MWHr. The worst forecasting obtained was 5.14% of MER in January, $2.97/MWHr of MAE in July and 5.14% of MAPE in January. The main cause of higher forecasting error in this month was due to higher no of spikes and outliers in New York market data. Table II also indicates the MAPE values for the 2011–2012 test dataset which gives the performance irrespective of the market numerical values.

The lower half of Figure 3 depicts the days with the best and worst forecasts in the 2011–2012 testing dataset. It is apparent that for the NYISO market our model produced more accurate forecasts.

2) ANEM Dataset: In case of 2011–2012 dataset, the worst performance was in the months of January-March with 15.28% MER in the month of February and best performance of 3.95% MER in the month of May. The worst and the best MAPEs were 13.53% in February and 4.25% in September respectively. There is a slight increase in S.D. which indicate that the errors in the years 2011–2012 are much more deviated from mean error. This is because of improvement in the forecasting accuracy for few months in 2011–2012 dataset. For this latest data our approach shows better performance with the increased accuracy of 1.8% MER, $0.89/MWHr MAE and more than 2.5% of MAPE, as shown in Table II. The worst and the best forecasted days for the years 2011–2012 are depicted in the lower half of Figure 4.

IV. CONCLUSION AND FUTURE WORKS

Electricity price forecasting in deregulated electricity market is essential to facilitate the decision making process. Though many research carried out in this field, significant improvements are yet to be performed. We proposed an ANN model using features extracted and selected from historical price data. In our experiments, we performed comparative analysis with a state-of-the-art method called PSF, and it was observed that our method offered better forecasting accuracy. We performed analysis both on 2006 and 2011–12 data and the results proved that our model can forecast accurately and robustly in the presence of noise. For future work, we intend to incorporate additional features such as gas prices, method of electricity generation, electricity demand and supply, etc. into our method. In addition, we plan to investigate a least-squares SVM-based method as in [6] for price forecasting.

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