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BINARY CLASSIFICATION OF DAY-AHEAD DEREGULATED ELECTRICITY MARKET PRICES USING NEURAL NETWORK INPUT FEATURED BY DCT

S. Anbazhagan[1] and N. Kumarappan[2]
Department of Electrical Engineering, Faculty of Engineering and Technology, Annamalai University, India
E-mail: [1]s.anbazhagan@gmx.com and [2]kumarappan_n@hotmail.com

Abstract
There is a general consensus that the movement of electricity price is crucial for electricity market. The binary electricity price classification method is as an alternative to numerical electricity price forecasting due to high forecasting errors in various approaches. This paper proposes a binary classification of day-ahead electricity prices that could be realized using discrete cosine transforms (DCT) based neural network (NN) approach (DCT-NN). These electricity price classifications are important because all market participants do not to know the exact value of future prices in their decision-making process. In this paper, classifications of electricity market prices with respect to pre-specified electricity price threshold are used. In this proposed approach, all time series (historical price series) are transformed from time domain to frequency domain using DCT. These discriminative spectral co-efficient forms the set of input features and are classified using NN. The binary classification NN and the proposed DCT-NN were developed and compared to check the performance. The simulation results show that the proposed method provides a better and efficient method for day-ahead deregulated electricity market of mainland Spain.

Keywords:
Price Forecasting, Discrete Cosine Transforms, Neural Network, Binary Electricity Price Classification, Electricity Market

1. INTRODUCTION

In a de-regulated electric power industry, the electricity prices play a key role for market participants. The main objective of market participants is to ensure a transparent, professional and cost-effective market. Since the beginning of floating electricity prices, electricity price forecasting has become one of the main endeavors for researchers and practitioners in energy market [1]. The daily load curves have similar load patterns, whereas the electricity price movement shows very great volatility among all commodities [2]. Electricity price can rise to tens of or even hundreds of times its normal values at some periods. Sometimes, it may drop to zero or even to negative values at other periods [3], [6]. The key uncertainties associated with those electricity prices are fuel prices, future addition of generation and transmission capacity, regulatory structure and rules, future demand growth, plant operations and climate changes [4].

From these many factors are impacting electricity price, in which some factors are more important than others. Besides, the factors, which impact price, they consider are very limited, just including historical price and system load [5]. Therefore, numerous data-driven approaches have been proposed for modeling and forecasting day-ahead electricity market prices [6]–[20].

The reported price forecasting errors generally range from approximately 5% to 36% and vary based on the technique used and the market analyzed. This range of error, however, is relatively high when compared to that of short-term electric load forecasting where errors usually range from 1% to 3% [21].

It is perceived from the existing literature that traditional price forecasting approaches are generally developed for numerical prediction or point-forecasting. That is, existing approaches try to predict the exact value of prices at future hours by approximating the true underlying price formation process. However, not all market participants need to know the exact value of future prices in their decision-making process. Many demand-response products are designed having certain thresholds for electricity prices in mind, such as the hour-ahead dispatchable load program in the Ontario market. Another example of threshold-based decision making can be found in electricity consumers with on-site generation facilities. These facilities only purchase electricity from the grid if the electricity market prices are below the marginal cost of operating the on-site electricity generation equipment. In these types of applications where the exact value of prices is not primarily required, the point-price forecasting problem can be reduced to price classification sub problems in which the class of future prices is of interest [21].

Electricity price classification has become an important research area in electrical engineering in recent years. Among the different approaches of classification systems, application of artificial neural network (ANN) input featured by discrete cosine transform (DCT) has been adopted in this paper because of its ability to learn complex and non-linear relationships that are difficult to model with conventional approaches.

This paper proposes a DCT input featured NN (DCT-NN) approach to classify next-week prices in the electricity market of mainland Spain. The day-ahead price classification method is as an alternative to numerical price forecasting. In binary price classification, predictions are made with respect to whether the price is above or below pre-specified price thresholds defined by users based on their operation and planning objectives. Price classification is specifically useful when the exact value of future prices is not critically important [21]. The main contribution of this paper is proposing a binary classification of day-ahead electricity prices that could be realized using DCT input featured multilayer neural network (MLNN), trained by the Levenberg-Marquardt (LM) algorithm.

The rest of the paper is organized as follows. The section 2 presents data source and proposed approach to bifurcate the electricity prices using their dataset. Section 3 presents the numerical results of proposed approach from mainland Spain market. Finally, the conclusions are presented in section 4.

2. METHODOLOGY

This section describes the data source and proposed DCT-NN binary classification model to day-ahead prices in mainland Spain electricity market.

2.1 DATA SOURCE

In order to perform the research reported in this paper, the electricity prices data taken from mainland Spain's daily trading reports, presented on a monthly basis were used. The Spain data set consists of market clearing price (MCP) [24]. Different sets of lagged prices have been proposed as input features for the binary price classification. The lags of P_{h-1}, P_{h-2}, P_{h-3}, P_{h-24}, P_{h-25}, P_{h-48}, P_{h-49}, P_{h-72}, P_{h-73}, P_{h-96}, P_{h-97}, P_{h-120}, P_{h-121}, P_{h-144}, P_{h-145}, and P_{h-168} are transformed from time domain to frequency domain using DCT in which considered as the input features for the proposed approach.

Binary classification thresholds are considered for the mainland Spain market for the year 2002: $T_1 = 0$, $T_2 = 37$ and $T_3 = 158$ with all in euro per megawatt hour. T_1, T_2 and T_3 are the price floors, annual average and price cap of the prices in mainland Spain. Normally, the price thresholds based on their own operating criteria were defined by the users. For the above price thresholds, the binary class distribution is

- Class 1: (Prices between T_1 and T_2)
- Class 2: (Prices between T_2 and T_3)

For binary electricity price classification, a target price that belongs to class 1 are applied with target as -1 and target prices that belongs to class 2 are applied with target as 1.

All patterns have sixteen features. These features are DCT transformed lagged prices.

2.2 BINARY CLASSIFICATION OF ELECTRICITY PRICES USING DCT-NN APPROACH

The proposed DCT-NN approach to bifurcate the electricity prices is based on a coordination of DCT and NN. In this approach, all time series (historical price series) are first transformed from time domain into a frequency domain using DCT. This step is crucial because it helps reducing the correlation between the features in time domain and in revealing the hidden information about the series. Then, these discriminative spectral co-efficient forms the set of input features and are classified using NN. Finally, NN classify the future behavior of the prices that classify the actual prices.

2.2.1 Discrete Cosine Transform:

In most real world time series, consecutive values of a time series are usually not independent, but highly correlated. This makes it difficult to develop effective feature selection techniques that work directly on the time series data. To alleviate the problem, time series can be transformed from time domain into another domain in order to de-correlate the time features and reveal the hidden structure of the series. This paper, describes the DCT time series transformation technique.

The DCT attempts to de-correlate the time series. After de-correlation each transformed co-efficient can be encoded independently without losing efficiency. DCT is a Fourier related transform is similar to discrete Fourier transform, but uses only cosine functions instead of using both cosines and sines. It transforms the input signal from time domain to frequency domain, which highlights the periodicity of the signal.

The DCT definition of a 1-D (one dimension) sequence of $f(x)$, length N is,

$$C(u) = \alpha(u)\sum_{x=0}^{N-1} f(x)\cos\left[\frac{(2x+1)u\pi}{2N}\right], \tag{1}$$

for $x = 0,1,2, \ldots N-1$. In Eq.(1), $\cos\left[\frac{(2x+1)u\pi}{2N}\right]$ is called forward DCT transformation kernel. In $C(u)$ for $u = 0,1,2,\ldots N-1$ in Eq.(1) are called DCT transform coefficients of $f(x)$.

In this approach, the inverse transformation is not used. In Eq.(1), $\alpha(u)$ is defined as,

$$\alpha(u) = \begin{cases} \sqrt{\frac{1}{N}} & for \quad u = 0 \\ \sqrt{\frac{2}{N}} & for \quad u \neq 0, \end{cases} \tag{2}$$

It is clear from the Eq.(1) that $u = 0$, $C(u=0) = \sqrt{\frac{1}{N}}\sum_{x=0}^{N-1} f(x)$. Thus, the first transform co-efficient is the average value of the time series. In literature, this value is referred to as the DC co-efficient. All other transform co-efficient are called the AC co-efficient.

In this paper, the DCT is used. It is chosen because it offers the following desirable properties:

1. DCT co-efficient are always real numbers;
2. DCT can handle effectively, the time series with trends;
3. When successive values are highly correlated, DCT achieves better energy concentration.

The 1-D DCT employed in this paper utilizes the DCT function implemented in MATLAB. Detailed information about the realization of the 1-D DCT can be found in the signal processing toolbox part of MATLAB documentation.

2.2.2 Neural Networks:

The ANN models are trained in such a way that a particular input leads to a specific target output. There are generally four steps in the training and testing process (1) assembling the training data, (2) creating the network, (3) training the network, and (4) computing the network response to new inputs.

In this paper, the MLNN is selected as NN type with LM training. The MLNN binary classification model with one hidden layer is used for the electricity price classification. The MLNN binary classification model (with one input layer, one hidden layer and one output layer) is shown in Fig.1. The hidden layer neurons (12 neurons) and the output layer neuron (1 neuron) use non-linear logarithmic-sigmoid and pure linear activation functions respectively. In this system, sixteen inputs are featured, and only one output is used to classify the binary electricity price classification. Equations used in the MLNN binary classification model with only one hidden layer are shown in Eq.(3) and Eq.(4).

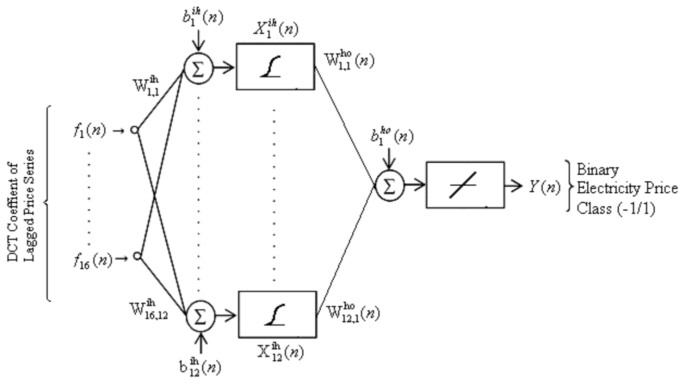

Fig.1. Implementation of DCT-NN for Binary Electricity Price Classification

Outputs of the hidden layer neurons are:

$$\vec{X}^{ih}(n) = 2/\left(1+\exp\left(-2*\left(W^{ih}(n)*\vec{f}(n)+\vec{b}^{ih}(n)\right)\right)\right)-1, \quad (3)$$

Output of the network is:

$$Y(n) = W^{ho}(n)*\vec{X}^{ih}(n)+b^{ho}(n), \quad (4)$$

where, $W^{ih}(n)$ are the weights from the input to the hidden layer and $\vec{b}^{ih}(n)$ are the biases of the hidden layer, $W^{ho}(n)$ are the weights from the hidden layer to the output layer and $b^{ho}(n)$ is the bias of the output layer, $\vec{f}(n)$ values are the input features. $Y(n)$ value is the output for the binary electricity price class, and n is training pattern index.

The back-propagation (BP) algorithm is widely recognized as a powerful tool for training of the MLNNs. But, since it applies the steepest descent method to update the weights, it suffers from a slow convergence rate and often yields suboptimal solutions. A variety of related algorithms have been introduced to address that problem and a number of researchers have carried out comparative studies of MLNN training algorithms. LM training algorithm used in this paper is one of the fastest types of these algorithms. Detailed computational issues about the application of the training algorithms to MLNN models can be found in reference [22].

The MLNN with LM binary classification model employed in this paper utilizes the newff function implemented in MATLAB. Detailed information about the realization of the MLNN with LM model can be found in the neural network toolbox part of MATLAB documentation.

2.3 IMPLEMENTATION PROCEDURE OF DCT-NN BINARY CLASSIFICATION MODEL

As previously described, electricity price is a nonlinear, time variant and multi-variable function. For instance, electricity price depends on its previous values, load values, available generation, etc. It is very hard for a single NN to capture correct input/output mapping function of such a signal in all time periods [23]. However, our experience shows that different electricity price classifications can usually cover deficiencies of each other for price forecast provided; a correct data flow is constructed among them. Some researcher proposed parallel and classification structures for this purpose [3]. A new classification procedure of MLNN binary classification model shown in Fig.2 is proposed in this paper.

The procedure outlined in Fig.2 and a detailed explanation of above procedure is given below.

1. *Apply DCT*: First, the input features (historical prices) are transformed from time domain to frequency domain using DCT of the Eq.(1).
2. *Preprocessor*: The input features (DCT transformed historical prices) and target output (binary electricity price class) are linearly normalized in the range of {-1, 1}.
3. *MLNN Binary Classification Model*: The binary price classification model for each of the considered weeks, the hourly DCT transformed historical prices of the past 42 days previous to the day of the week are trained and tested using MLNN of Eq.(3) and Eq.(4), trained by the LM algorithm.
4. *Postprocessor*: The output from the MLNN binary classification model was de-normalized.
5. *Binary Classification*: During binary classification, output of binary class is compared. The threshold is 0, the classes below threshold output will represent class 1 and above and equal to threshold output will represent class 2. In this paper each NN binary classification models are modeled as a MLNN, and DCT-NN network. The actual electricity price class is compared with the NN binary classification models output binary electricity price class. If it does not belong to the same class, then increment the number of misclassification rate. This procedure is repeated until each of the considered weeks.
6. *Performance Evaluation*: The performance of the trained network is then evaluated by mean percentage classification error and percentage classification accuracy. These are used to measure the classification error.

3. NUMERICAL RESULTS

This section describes the case study of Spanish electricity market price classification for the year 2002 using proposed NN binary classification models.

3.1 CASE STUDIES

The methodology described above has been applied to classify the binary electricity price classification of Spanish market.

Day-ahead electricity market of Spanish, in year 2002 is used as test case in binary price classification. For the sake of comparison, four weeks of February, May, August and November 2002 are selected, i.e., weeks with particularly good price behavior are deliberately not chosen [4]. In order to evaluate the proposed binary classification models, the most volatile prices, are employed for price classification in this paper.

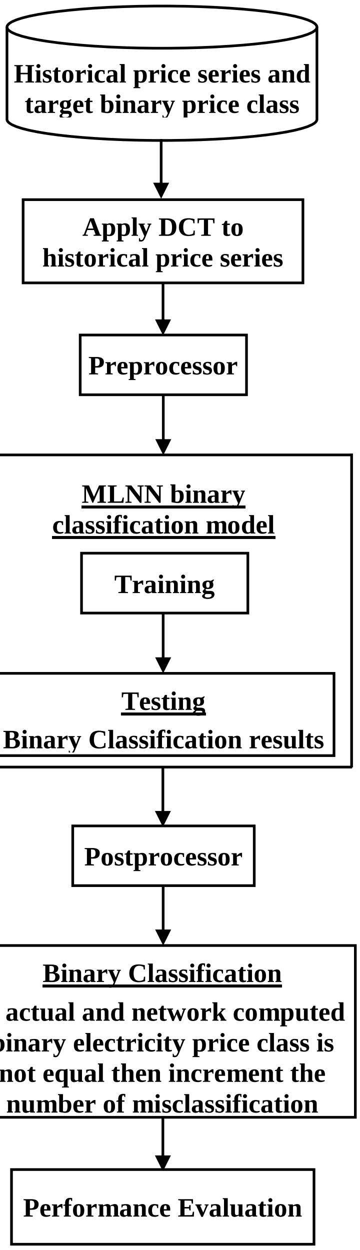

Fig.2. Binary Classification Procedure of DCT-NN

To build the binary price classification model for each of the considered weeks, the information available includes hourly historical prices of the 42 days previous to the day of the week whose prices are to be classified. Very large training sets are not used to avoid overtraining during the learning process.

For the Spanish market, the winter week is from February 18 to February 24, 2002, the spring week is from May 20 to May 26, 2002, the summer week is from August 19 to August 25, 2002 and the fall week is from November 18 to November 24, 2002; the historical data available includes hourly prices from January 7 to February 17, 2002, from April 8 to May 19, 2002, from July 8 to August 18, 2002 and from October 7 to November 17, 2002 are used to classify the respective week.

In this paper, the input features (DCT transformed historical prices) and target output (binary price class) are linearly normalized in the range of {-1, 1}. The output from the MLNN binary classification model was de-normalized before being presented in performance evaluation.

The performance of the trained network is then evaluated by comparison of the network output with its actual value via statistical evaluation indices. The mean percentage classification error (MPCE) and percentage classification accuracy (PCA) are used as the overall measures of classification error in this paper.

The MPCE can be defined as,

$$MPCE = 100 \times \left(\frac{N_{mc}}{N_{tot}} \right), \tag{5}$$

The PCA is given by,

$$PCA = \left(\frac{N_{tot} - N_{mc}}{N_{tot}} \right) \times 100, \tag{6}$$

where, N_{mc} and N_{tot} are the number of misclassified and total number of classified hours, respectively.

3.2 BINARY CLASSIFICATION OF ELECTRICITY PRICES WITH NN APPROACH

In NN binary classification model, the architecture and training are determined using stochastic approach. Several attempts were made until the proper number of hidden layers and numbers of neurons in hidden layer were reached. The network architecture selected after many attempts produced minimal error in both training and testing.

The NN binary classification model have input layer composed of sixteen neurons, hidden layer composed of twelve neurons and output layer with one neuron (binary price class). The MLNN is selected as the network type with LM training. The NN binary classification model is implemented using the MATLAB neural network toolbox. The size of the input pattern is 16 (historical price series) x 1008 (42 days training period x 24 hours), and the size of the target pattern is 1 (binary price class) x 1008 in this NN binary classification model.

The MPCE and PCA obtained by NN binary classification model to electricity price classification were presented in Table.1 for Spanish market in year 2002. The first column indicates the classification week, the second column indicates MPCE and the third column shows the PCA. It is observed that the MPCE and PCA obtained using NN approach for the Spanish electricity market has an average value of 4.2% and 95.83%.

3.3 BINARY CLASSIFICATION OF ELECTRICITY PRICES WITH DCT-NN APPROACH

For the sake of a fair comparison, the DCT-NN binary classification model also have input layer composed of sixteen neurons, hidden layer composed of twelve neurons and output layer with one neuron. The MLNN is selected as the network type with LM training. The DCT-NN binary classification model is implemented using the MATLAB neural network toolbox. The size of the input pattern is 16 (DCT transformed historical price series) x 1008 (42 days training period x 24 hours), and the size of the target pattern is 1 (binary price class) x 1008 in DCT-NN binary classification model.

The Fig.3 to Fig.5 shows the performance, training state and regression plot for spring week tested in DCT-NN binary classification model. From Fig.3, the performance of DCT-NN binary classification model shows the gradual reduction of mean square error (mse) values that epoches after epoches. From this observation, we can conclude that the DCT-NN binary classification model learns for the training data to map the input and output parameters at epoch 14. For training state, Fig.4 shows the very low *gradient* and *mu* values and *validation checks* are performed for stopping the DCT-NN training. The *gradient* will become very small as the training reaches a minimum of the performance. If the magnitude of the *gradient* is less, the training will stop. The *gradient* is decreased rapidly to 0.12195 at epoch 14. The *mu* controls how much the weights are changed on each epoches. The *mu* value is as low as 10e-6 or as high as 0.1. It can be expected that too small of a value will cause the network to converge too slowly and too large of a value will cause the convergence to be erratic, and will exhibit chaotic oscillation around the final solution. The *mu* is decreased rapidly to 0.001 at epoch 14. The number of *validation checks* represents the number of successive iterations that the validation performance fails to decrease. If this number reaches 6 (the default value), the training will stop. The *validation checks* are increased rapidly to 6 at epoch 14. For regression plot, from Fig.5 it is observed that the DCT-NN binary classification model achieves good performance for training, validation, test and overall data with help of R value (correlation coefficient) which is equal to 0.89 on an average. It performs a linear regression between the network response output and the corresponding targets, and then computes the correlation coefficient (R-value) between the network response and the target value. If R = 1 it means perfect correlation.

The MPCE and PCA obtained by proposed DCT-NN binary classification model to electricity price classification were presented in Table.1 for Spanish market in year 2002. The first column indicates the classification week, the fourth column indicates MPCE and the fifth column shows the PCA. It is observed that the MPCE and PCA obtained using proposed DCT-NN approach for the Spanish electricity market has an average value of 3.5% and 96.58%. The MPCE and PCA results confirm that the proposed DCT-NN binary classification model is capable of classifying the electricity market prices efficiently.

Table.1. Statistical Analysis for Four Weeks of Spanish Market in Year 2002

Classification Week	NN Approach		DCT-NN Approach	
	MPCE	PCA	MPCE	PCA
Winter	3.6	96.43	3.0	97.02
Spring	3.0	97.02	1.8	98.21
Summer	5.4	94.64	4.2	95.83
Fall	4.8	95.24	4.8	95.24
Average	4.2	95.83	3.5	96.58

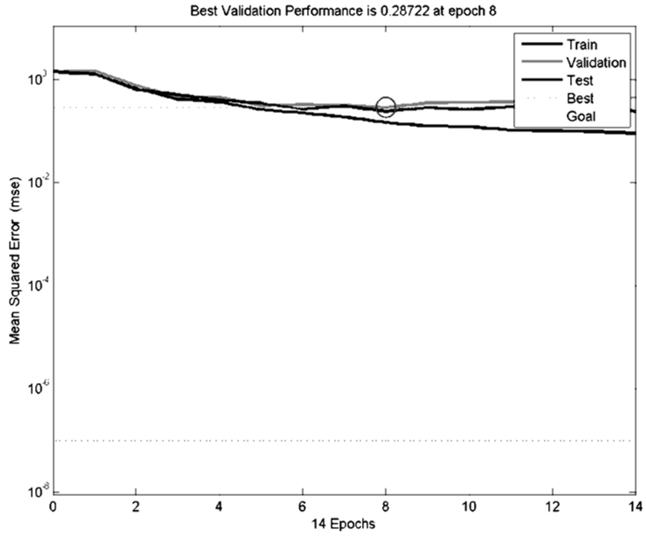

Fig.3. Performance Plot of DCT-NN for Spanish Spring Week to Binary Price Classification

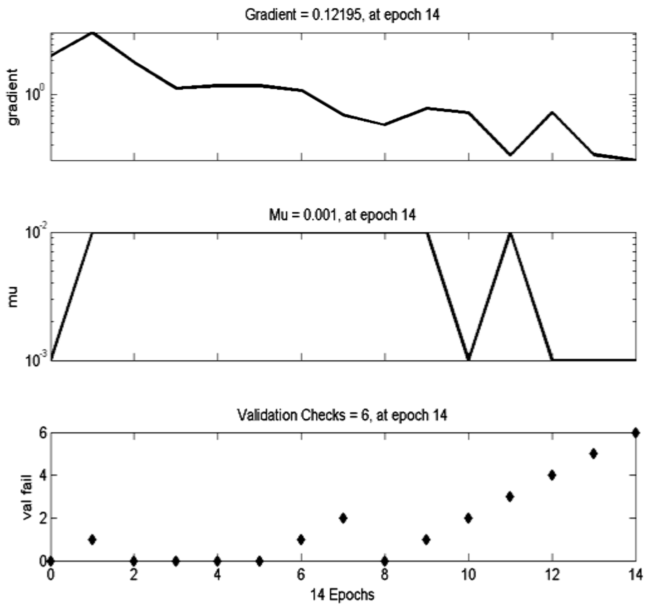

Fig.4. Training State Plot of DCT-NN for Spanish Spring Week to Binary Price Classification

3.4 THE COMPARISON OF BINARY PRICE CLASSIFICATION

Table.1 gives statistical analysis for four weeks obtained with the NN and DCT-NN approaches on Spanish market for the year 2002.

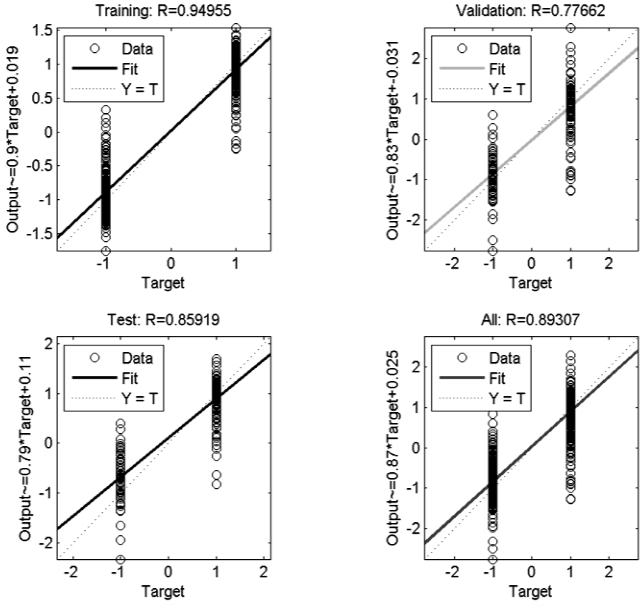

Fig.5. Regression Plot of DCT-NN for Spanish Spring Week to Binary Price Classification

Table.1 shows the minimum MPCE is 1.8% and maximum PCA is 98.21% occurred in spring week of DCT-NN approach for the binary price classification when compared with NN approach on Spanish market. From the same Table.1, it is observed the minimum MPCE and maximum PCA is 3.5% and 96.58% respectively occurred on an average in DCT-NN approach for binary price classification when compared with NN approach for all the four weeks of Spanish market in year 2002.

Improvement in the average MPCE of the proposed DCT-NN approach with respect to the NN approach is 0.7% and improved percentage average error of MPCE is 16.7% on Spanish electricity market. So, we can easily say that DCT-NN approach possesses better classifying abilities than the NN approach and its performance was least affected by the price volatility. Finally, the proposed DCT-NN approach provides a very powerful tool of easy implementation for electricity price classification.

The simulations were carried out in AMD processor with 2GHz and 1GB RAM. Moreover, the proposed approach presents lower modeling complexity: the average computation time is less than 15ms. In a deregulated electricity market, the fast classification of prices is also important for real-life applications.

4. CONCLUSION

This paper presented a comprehensive model for day-ahead electricity price classification using a DCT input featured artificial neural network approach in the mainland Spain deregulated markets. The electricity price depends on its previous values (historical values) and load values. In binary electricity price classification, predictions are made with respect to whether the price is above or below the pre-specified price thresholds used. To verify the binary electricity price classification ability of the proposed approach, yielding an average weekly MPCE and PCA for the Spanish electricity was close to 3.5% and 96.58% which shows a better capability to improve the problem of classifying price spikes. The test results showed that the proposed binary classification model, especially the MPCE and PCA results of the proposed DCT-NN binary classification model is a good tool for binary price classification in terms of efficiency as well as heuristic compared to NN binary classification model. The research work is underway in order to develop better feature selection algorithm for different power markets and classification models.

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