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Electricity Price Forecasting: A Comparative Analysis with Shallow-ANN and DNN

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Abstract—Electricity prices have sophisticated features such as high volatility, nonlinearity and high frequency that make forecasting quite difficult. Electricity price has a volatile and non-random character so that, it is possible to identify the patterns based on the historical data. Intelligent decision-making requires accurate price forecasting for market traders, retailers, and generation companies. So far, many shallow-ANN (artificial neural networks) models have been published in the literature and showed adequate forecasting results. During the last years, neural networks with many hidden layers, which are referred to as DNN (deep neural networks) have been using in the machine learning community. The goal of this study is to investigate electricity price forecasting performance of the shallow-ANN and DNN models for the Turkish day-ahead electricity market. The forecasting accuracy of the models has been evaluated with publicly available data from the Turkish day-ahead electricity market. Both shallow-ANN and DNN approach would give successful result in forecasting problems. Historical load, price and weather temperature data are used as the input variables for the models. The data set includes power consumption measurements gathered between January 2016 and December 2017 with one-hour resolution. In this regard, forecasting studies have been carried out comparatively with shallow-ANN and DNN models for Turkish electricity markets in the related time period. The main contribution of this study is the investigation of different shallow-ANN and DNN models in the field of electricity price forecast. All models are compared regarding their MAE (Mean Absolute Error) and MSE (Mean Square) results. DNN models give better forecasting performance compare to shallow-ANN. Best five MAE results for DNN models are 0.346, 0.372, 0.392, 0,402 and 0.409.

Keywords—Deep learning, artificial neural networks, energy price forecasting, Turkey.

I. Introduction

ENERGY price forecasting is an interdisciplinary field and includes diverse communities such as artificial intelligence, finance, electrical engineering and meteorological science. Electricity pricing plans include complex process, and electricity has its own unique characteristics. Electricity production is unstorable and there must be a constant balance between electricity consumption and production for the stability of the electrical system [1].

Several methods have been proposed for forecasting electricity price, which are agent based modeling [2], [3], time series [4], [5], artificial neural networks [6], [7], generalized autoregressive conditional heteroskedasticity (GARCH) models [8], [9], wavelet models [10], [11] and hybrid models [12], [13]. Artificial neural networks have received more attention due to its simplicity, easy implementation and performance [14]. These models with advantages and disadvantages have been applied for the electricity price forecasting. Aggarval et al. classified electrical price forecasting models in game theory models, time series models and simulation models. Artificial intelligence models are classified under the subhead of the time series models. Electricity price models classified by Aggarval et al. are shown in Fig. 1, [15].

Neural networks can be divided into two groups as feed forward and recurrent networks. Feed forward networks do not have loops. Several layers or one layer is considered the same in terms of neural networks a decade ago. But now, DNN have many layers so that the network is called deep neural networks and a network with a single hidden layer is called shallow-ANN.

Shallow-ANN and DNN have successful results against sudden input changes. This makes superior Shallow-ANN and DNN price forecasts to traditional forecasting techniques. Also it is necessary to process the data for use, but it does not require certain rules like traditional methods need.

The success of deep learning in the landscape of machine learning poses a question: why are multi-layer networks (DNN) better than shallow-ANN (one-hidden layer) networks. Shallow-ANN architecture would be inefficient and require a lot more neurons for the same performance compared to DNN. The aim of this study is to investigate electricity price forecasting performance of shallow-ANN and DNN models in Turkey electricity market.

This paper is organized as follows. Section I gives some of models used for electricity price forecasting. Section II gives information about shallow-ANN and DNN. Section III shows models that are created and tested with using Turkish electricity market data. Finally, results are discussed in conclusion.

II. Models

Artificial neural networks inspired by brain work are non-mathematical parametric and non-linear models that match inputs and outputs [16]. The usage of neural networks for forecasting goes back to 1964. Hu used linear network for weather forecasting in 1964 [17]. The neurons are the basis of the artificial neural networks. The learning process shapes the connections between the neurons in neural networks. The structure of single neurons is shown in Fig. 2. Brain-inspired neuron has a processing node, connections from (‘dendrites’) and connections to (‘axons’) other neurons. The neurons are

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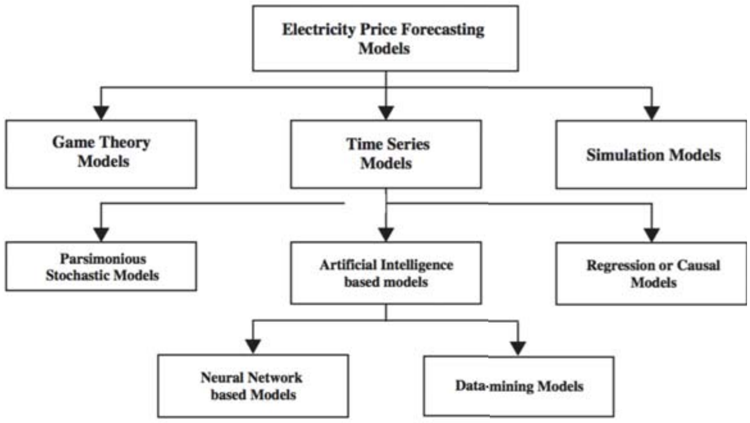

Source: (Aggarwal, 2009) [15]

Fig. 1 Electricity Price Modeling Approaches

arranged in layers. The layers counts define shallow-ANN or DNN architecture. The layer numbers, learning algorithms and layers connections types are important in making network architecture decisions.

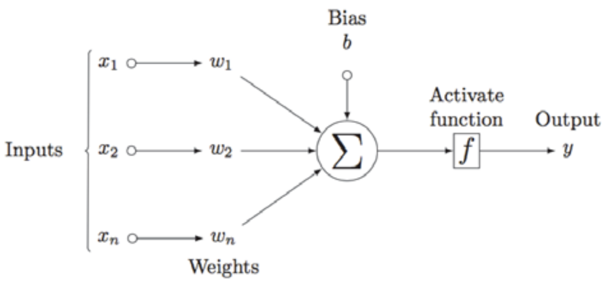

Fig. 2 Mathematical Model of a Nonlinear Neuron

The following equation describes a single neurons calculation.

$$y = f(\sum_{i=1}^{n} x_i w_i + b) \tag{1}$$

where x_1,x_2, ...x_n are the input variables;w_1,w_2,...w_n are the weights of neuron, b is the bias,f is activate function and y is the output of neuron.

Artificial neural networks are grouped into two categories as feed-forward networks and recurrent networks. Feed forward neural networks and recurrent neural networks are popular forecasting methods. Feed forward neural networks neuron connections do not form a loop. Feed forward neural networks do not have backward link to the neurons in the previous layer. If there is backward link to the neurons in the previous layer, it becomes RNNs. The difference between feed forward neural networks and recurrent neural networks is shown in Fig. 3

Deep learning models are learning circuits with variable depth, generally larger than two hidden layer depths. The more depth layer can provide deep abstraction [18]. The argument in [19] is that a deep architecture is able to compute some functions much more efficiently than a shallow one. Shallow neural architectures can be very inefficient in terms of the number of computational units.

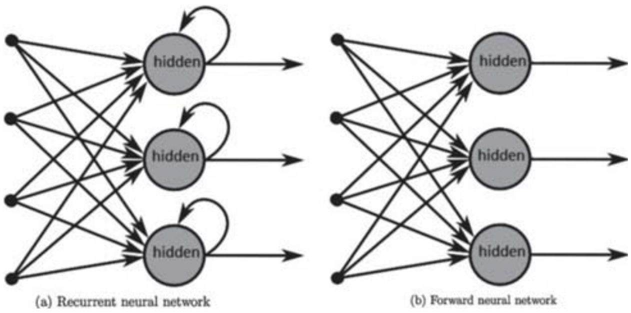

Fig. 3 Recurrent neural networks vs Feed forward neural networks

The Long Short Term Memory (LSTM) enhanced from recurrent neural networks. Unlike feed forward neural networks, recurrent neural network use also temporal information. The LSTM has been used for solving long-term dependency problems and provides good forecasting results [20]. LSTM is explicitly designed to avoid the long-term dependency problem. LSTM can remember information for long periods of time. LSTM has input gate, output gate, forget gate, cell, output activation function and peephole connections. The input gate allows changing the state of the memory cell. The state of the memory cell is allowed by the output gate to have an effect on other neurons. Forget gates takes out the guarantee that LSTM can persist gradients and not vanish. Deep neural networks have some advantages compared to shallow ones. Deep neural networks can be easily adapted to different problems because of their standard architecture [21]. Fig. 4 shows LSTM block and Fig. 5 shows LSTM equations. See the Greff et al. study on LSTM for detailed information [22]

Shallow-ANN and DNN also have common features such that the layer and neuron counts. The layer and neuron counts are the key to modeling neural network structures. An intuitive method has been used to select the number of hidden neurons in the Shallow-ANN and DNN. Due to the fact that it is a constantly developing area, different algorithms and architectural structures are being proposed in DNN.

Shallow-ANN and DNN have same design procedure. In

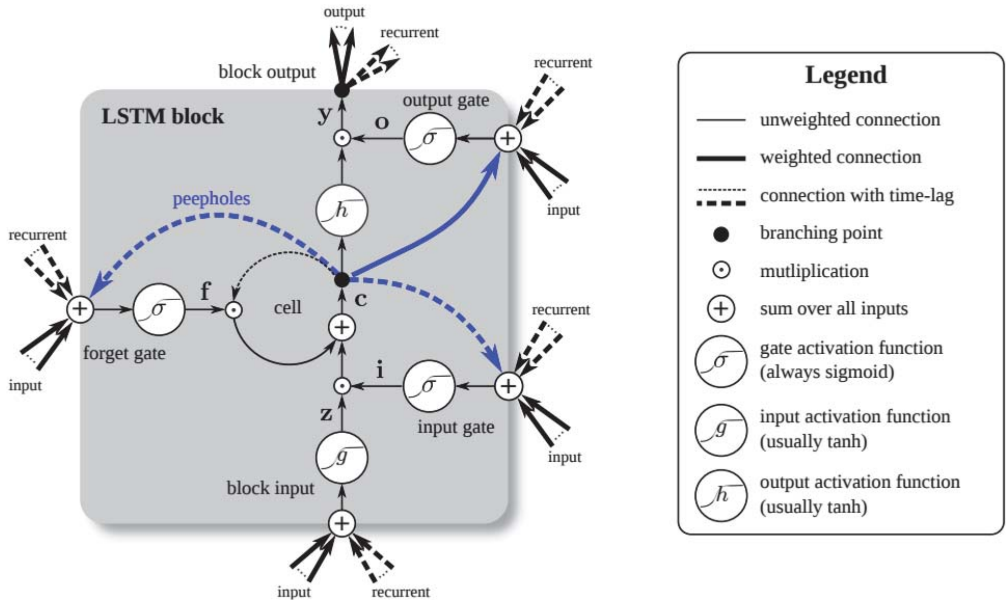

Fig. 4 LSTM Block

$$
\begin{aligned}
\mathbf{z}^t &= g(\mathbf{W}_z\mathbf{x}^t + \mathbf{R}_z\mathbf{y}^{t-1} + \mathbf{b}_z) && \textit{block input}\\
\mathbf{i}^t &= \sigma(\mathbf{W}_i\mathbf{x}^t + \mathbf{R}_i\mathbf{y}^{t-1} + \mathbf{p}_i \odot \mathbf{c}^{t-1} + \mathbf{b}_i) && \textit{input gate}\\
\mathbf{f}^t &= \sigma(\mathbf{W}_f\mathbf{x}^t + \mathbf{R}_f\mathbf{y}^{t-1} + \mathbf{p}_f \odot \mathbf{c}^{t-1} + \mathbf{b}_f) && \textit{forget gate}\\
\mathbf{c}^t &= \mathbf{i}^t \odot \mathbf{z}^t + \mathbf{f}^t \odot \mathbf{c}^{t-1} && \textit{cell state}\\
\mathbf{o}^t &= \sigma(\mathbf{W}_o\mathbf{x}^t + \mathbf{R}_o\mathbf{y}^{t-1} + \mathbf{p}_o \odot \mathbf{c}^{t} + \mathbf{b}_o) && \textit{output gate}\\
\mathbf{y}^t &= \mathbf{o}^t \odot h(\mathbf{c}^t) && \textit{block output}
\end{aligned}
$$

Fig. 5 LSTM Equations

general, the artificial neural network design includes the following steps [16]:

- The architecture type selection
- The neurons in layers
- The layers selections
- The activation functions selections
- Data preprocessing methods
- Training and test datasets
- The training algorithm selections
- The performance measures selections

All above steps need decision to find best one. The selections in above steps significantly affect models performance. Training algorithms, activation functions, architecture types,layer counts, data preprocessing methods, performance measures and neurons number can change with new methods continuously.

III. Experimental Results

Historical load, price and weather temperature data are used as the input variables for the models. Electricity price data is publicly available and has been taken from the Energy Exchange Operations Authority of Turkey (EPIAS). The data set includes power consumption measurements gathered between January 2016 and December 2017 with one-hour resolution. Fig. 6 shows electricity price changes between 2016 and 2017. There are two spikes in this interval and these spikes adversely affect model performance.

TABLE I
Inputs Statistics

	Mean	Standard deviation(std)
τ_m (°C)	16	9,2
Load (MWh)	31,862	5775
Price (TL)	151,87	53,69

TABLE II
Performance Measurement Methods

Method	Algorithm
MAE	$\frac{1}{n}\sum_{t=1}^{n}\lvert A_t - F_t\rvert$
MSE	$\frac{1}{n}\sum_{t=1}^{n}(A_t - F_t)^2$

Table I shows models input statistics. The temperature, load and price data are used in this study. Electricity prices are significantly influenced by electricity load and weather.

Mean absolute error (MAE) and mean square error (MSE) are widely used in network performance. In this study, the mean absolute error (MAE) and the mean squared error(MSE) are used to compare shallow-ANN and DNN models. Table II shows MAE and MSE calculations. A_t indicates the real value and F_t indicates the estimated value.

DNN prove to be more advantageous than shallow-ANN since they can succinctly represent a significantly larger set of functions [23]. Our experimental results also support that DNN models give better results than shallow-ANN ones. Table III shows the best electricity price forecasting models according to MAE and MSE.

IV. Conclusion

Neural networks have become an increasingly used for electricity price forecasting. Deep neural networks are more efficient models in representing certain functions than shallow ones [24]. Shallow-ANNs approach has limited prediction

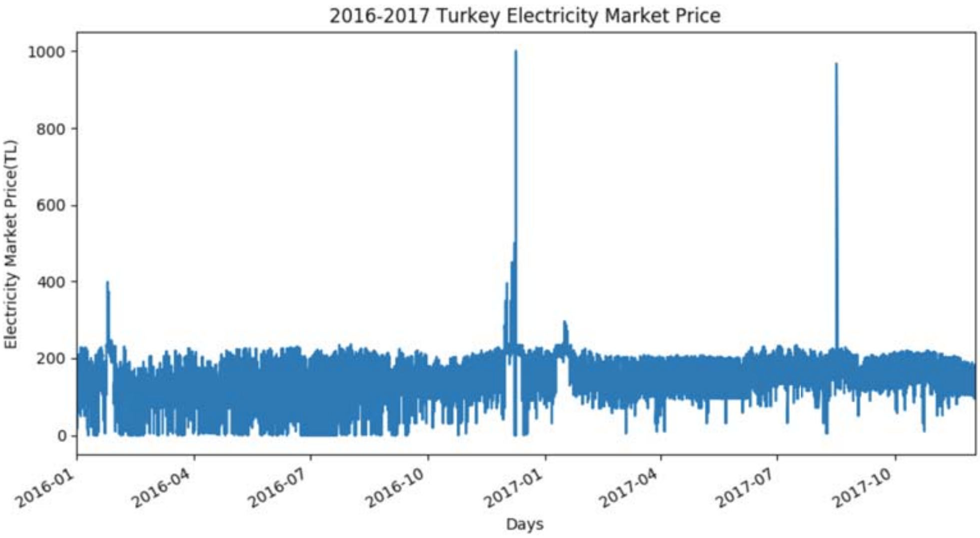

Fig. 6 Electricity Market Price

TABLE III
ELECTRICITY PRICE FORECASTING RESULTS

Model Name	Mean Absolute Error	Mean Squared Error
l-l0 l-50 d-0.1	0.346	0.256
l-30 l-50	0.372	0.280
l-20 l-15	0.392	0.296
l-20 l-50 d-0.1	0.402	0.309
l-10 l-50 l-10 d-0.1	0.409	0.313

performance because of redundant and irrelevant input variables and less efficient structure.

This study compares shallow-ANN and DNN models according to forecasting performance for Turkish day-ahead electricity market. Different shallow-ANN and DNN models have been applied to find out best MAE results. The deep neural networks thus offer a much more compact representation of the electricity price forecasting.

Different neural network architectures should applied to electricity price forecasting. AutoEncoders, Deep Belief Networks should be investigated in the next studies.

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