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Deep Learning for Renewable Power Forecasting: An Approach Using LSTM Neural Networks

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Abstract**—**Load forecasting has become crucial in recent years and become popular in forecasting area. Many different power forecasting models have been tried out for this purpose. Electricity load forecasting is necessary for energy policies, healthy and reliable grid systems. Effective power forecasting of renewable energy load leads the decision makers to minimize the costs of electric utilities and power plants. Forecasting tools are required that can be used to predict how much renewable energy can be utilized. The purpose of this study is to explore the effectiveness of LSTM-based neural networks for estimating renewable energy loads. In this study, we present models for predicting renewable energy loads based on deep neural networks, especially the Long Term Memory (LSTM) algorithms. Deep learning allows multiple layers of models to learn representation of data. LSTM algorithms are able to store information for long periods of time. Deep learning models have recently been used to forecast the renewable energy sources such as predicting wind and solar energy power. Historical load and weather information represent the most important variables for the inputs within the power forecasting models. The dataset contained power consumption measurements are gathered between January 2016 and December 2017 with one-hour resolution. Models use publicly available data from the Turkish Renewable Energy Resources Support Mechanism. Forecasting studies have been carried out with these data via deep neural networks approach including LSTM technique for Turkish electricity markets. 432 different models are created by changing layers cell count and dropout. The adaptive moment estimation (ADAM) algorithm is used for training as a gradient-based optimizer instead of SGD (stochastic gradient). ADAM performed better than SGD in terms of faster convergence and lower error rates. Models performance is compared according to MAE (Mean Absolute Error) and MSE (Mean Squared Error). Best five MAE results out of 432 tested models are 0.66, 0.74, 0.85 and 1.09. The forecasting performance of the proposed LSTM models gives successful results compared to literature searches.

Keywords**—**Deep learning, long-short-term memory, energy, renewable energy load forecasting.

I. Introduction

LOAD forecasting in energy markets is a basis for market decisions. Therefore, the success of electrical load estimates is a very important factor for decision makers. Load forecasting task in the electricity market is difficult due to the complexity of the market. This complexity arises from the instant nature of the electricity, complex market design and frequent regulatory interventions.

The rapid rise of industrialization within the last century has contributed to the growth of electricity consumption. With the liberalization of many electricity markets; utilities had to face to the fact that accurate load forecasting became a necessity. Forecasting the electricity load is crucial for market participants, which are generation companies, energy transactions and planners. Market participants with good load forecasting may have efficient utilization of electric energy. Similarly, economic load distribution and planning is based on electrical load forecasting. A proper load forecasting policy in the electricity industry is of the utmost important for the whole economy. Accurate load forecasting results in a great saving for electric utilities.

There are different types of power load forecasting models based on time horizon, algorithms and architecture types. According to time horizon, power load forecasting methods can be classified as long-term, medium-term and short-term methods. Short-term power load forecasting horizon ranges from hour to week. Medium-term load forecasting ranges from one week to one year, long-term power load forecasting covers more than a year. The long-term horizon assists the power planning supply. The medium-term horizon is used for maintenance of power networks and contract negotiations. The short-term horizon forecasting is used as operation and planning of power networks.

In last decades different algorithms were proposed to forecast electricity loads. Kalman filter [1], [2], autoregressive moving average [3], [4], linear regression analyses [5], [6], agent-based models [7], [8], support vector machines [9], [10], deep neural networks [11]- [13] are used to forecast electricity load.

Kankal et al. has examined studies related to energy forecasting for Turkey and has found ANN, swarm optimization, genetic algorithm approach, harmony search algorithm, ARIMA methods. Energy power forecasting studies on of Turkey have began in the 1960s and starting from 1984 econometrics models have been applied for forecasting purposes [14]. Kücükali and Barış developed a fuzzy logic electricity demand model for Turkey and showed electricity demand is strongly related to gross domestic product of the country. They also suggested that short-term electricity forecasting with economic performance would provide more reliable data for the policy makers [15]. Günay used a database (covering the years between 1975 and 2013) constructed including population, GDP per capita, inflation percentage, unemployment percentage, average summer temperature and average winter temperature to forecast the annual gross electricity demand of Turkey.

Vassilis et al. classified electricity load forecasting by traditional approach (linear regression, nonlinear regression, time series models and Kalman filters), computational

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approach (neural networks, support vector machines and fuzzy systems). They also suggested hybrid models for load forecasting by combining wavelet and neural networks [16]. Nazaeeruddin and Alfares's electric load forecast survey classified electricity load forecasting models as; multiple regression, least squares difference, adaptive load forecasting models, stochastic time series, fuzzy logic, neural networks, and knowledge-based expertise [17]. Lou and Dong classified load forecasting techniques as mathematical models, soft-computing techniques and hybrid of different techniques. They focused on uncertainty on load characteristic and proposed fuzzy variable and neural network combination for load forecast [18].

Deep Learning have been very hot in time series domains. Deep neural networks improve the performance of load forecasting by focusing on pre-training and parameter optimization.

Above models have the advantages and disadvantages. There are also hybrid architectures for the load power forecasting. The hybrid architectures are a combination of above algorithms.

The rest of the paper is organized as follows. Section II gives description of the deep neural networks and LSTMs. Section III provides experimental results and finally, results and some forward ideas are discussed in the conclusion.

II. Models

Renewable energy estimation in the electricity market is a complex process, which is influenced by interrelated events such as climate conditions, corporate and social events. There is no single and best model covering all power load forecasting potentials. Neural networks are preferred as a popular forecasting tool with a non-linear feature and complex input-output mapping facility [19].

Due to the increased use of renewable energy, it is necessary to forecast renewable energy production with advanced algorithms. During the last years, deep neural networks studies have gained momentum. Deep learning consists of multiple layers to learn representation of data with layers of abstraction. Reviews on deep learning methodologies can be found in [20]. Fig. 1 shows sample DNN structure.

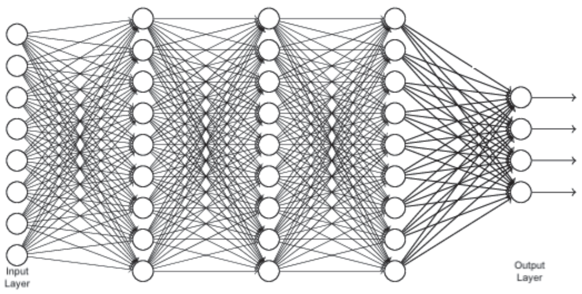

Fig. 1 Sample DNN

In this study, the effectiveness of a deep learning is investigated by establishing renewable electricity load forecasting models. The proposed methodology uses the LSTM algorithm. LSTM networks are a special kind of Recurrent Neural Networks (RNN). The RNN is trained using either recurrent learning or back-propagation. The RNN operates in conjunction with the previous state of the result or the previous more than one steps. The RNN model fails on vanishing gradient descent, LSTM compensates this failure. LSTM is a recurrent neural network that provides a model that can store information for time periods, especially those used to overcome the problems of vanishing gradient. LSTM is trying to solve the problem of training over retaining memory and long sequences. LSTMs solve the gradient problem by introducing a more gates. LSTMs has input gate, output gate, forget gate, cell, output activation function and peephole connections. Fig. 2 shows schematic of LSTM block [21] and Fig. 3 shows LSTM equations.

The input gate determines whether the input will be saved in the memory cell. The output gate determines if current memory cell will be output. The forget gate determines whether current contents of memory will be forgotten.

III. Experimental Results

Selecting an appropriate architecture is the first step to take when designing a forecasting model. To find the best models with LSTM algorithm in Turkey market, we have changed layer cell count and dropout. Models use publicly available data from the Turkish Renewable Energy Resources Support Mechanism. Data covers the days between 01.01.2016 and 31.12.2017, from this data hours between 01.01.2016-01.07.2017 was used for training the model, hours between 02.07.2017-31.12.2017 was used to test the model. Fig. 4 shows total renewable load data changes between 01.01.2016 and 31.12.2017. Python was used as a programming environment. The actual data and the forecasted data were compared through MAE results and MSE.

Fig. 5 shows wind, hydroelectric and geothermal energy. Waste to energy, solar energy and biomass energy is not included in this study.

The selection of the input variables can significantly affect network performance. In the short term, load depends on the weather (temperature, wind speed, precipitation, etc.) and historical load data. The optimal choice of input variables still remains an open question. Renewable energies used in this study are wind energy, geothermal energy and hydroelectric energy.

Innovations in wind energy, geothermal energy and hydroelectric energy are making renewable energies cost-compatitive. Wind energy is the most rapid and consistent deployment of power generating capacities and plays a larger role in renewable energies. Wind energy forecasting is difficult, due to its dynamic nature. Accurate wind power forecasts reduce the cost and mitigates the physical impacts of extreme weather on wind power systems.

Geothermal energy comes from reservoirs of steam and hot water. Geothermal energy is efficient and environmentally friendly types of renewable energy to generate electricity. Apart from being a clean source, geothermal energy is also suitable for load electricity generation. Also, geothermal energy has no shortage problems which sometimes occur with other types of energy generators.

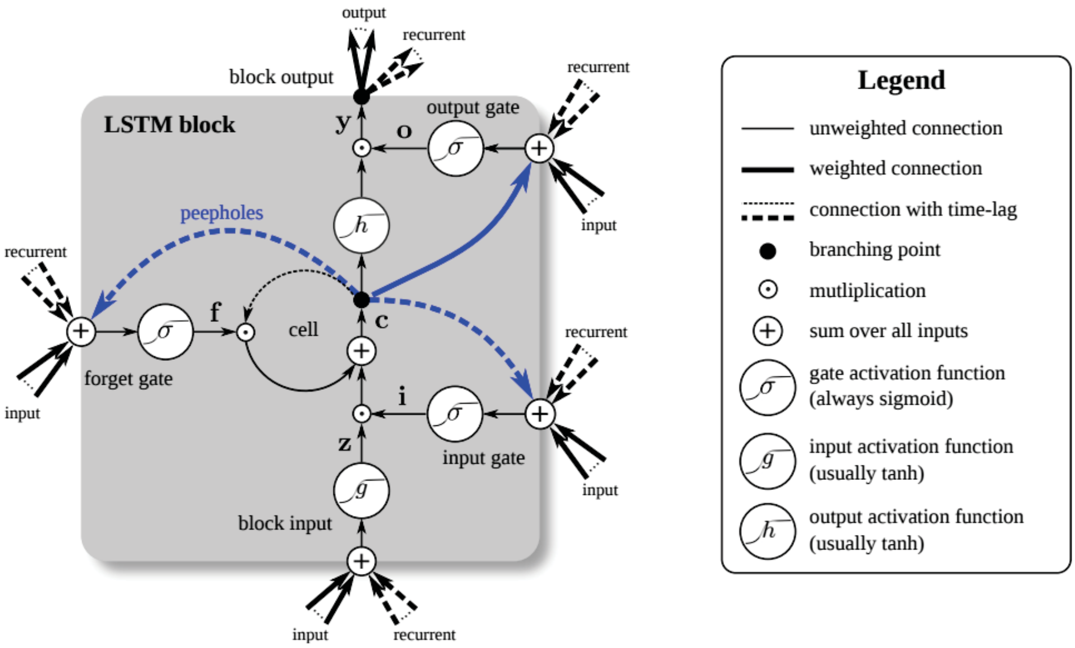

Fig. 2 LSTM Block

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

Fig. 3 LSTM Equations

TABLE II
ELECTRICITY LOAD FORECASTING RESULTS

Model Name	Mean Absolute Error	Mean Squared Error
l-50 l-15 d-0.1	0.660	0.647
l-10 l-10 l-15 d-0.1	0.748	0.818
l-5 l-50 l-10 d-0.2	0.753	0.843
l-10 l-20 l-10	0.854	1.088
l-30 l-10 l-10 d-0.2	1.096	1.767

Hydroelectric energy is produced from water falling. The falling water drives an electrical generator which converts the motion into energy. Hydropower plants can quickly go from zero power to maximum output so that hydroelectric energy can be injected into the electricity system faster than that of any other energy source. Hydroelectric energy has zero emissions, low running cost.

There is a common understanding that the weather information is the most important model entry used to estimate the load [22]. The demand is high in cold climates because electric heating is common. Similarly, demand is high in hot weather, which can be attributed to air-conditioning compriessors. This result in U-shaped function of the load with regard to the temperature [23]. Table I shows models input statistics.

TABLE I
INPUTS STATISTICS

	Mean	Standard deviation(std)
τ_m (°C)	16	9,2
Total Load (MWh)	31,862	5775
Renewable Load (MWh)	5090	1612

432 different models are created by changing layers cell count and dropout. Dropout is a popular regularization technique in deep neural networks. Dropout is a regularization method where connections of LSTM units are probabilistically excluded. The randomly selected neurons are dropout during training. The effect is that neural net neurons become more independent and less sensitive to the weight of neurons. Dropout is reducing overfitting and increasing performance.

ADAM algorithm with convergence and lower error rates is better than SGD (stochastic gradient descent). ADAM uses both first-order moment mt and second-order moment. ADAM combines the advantages of adaptive gradient (AdaGrad) and root mean square propagation(RMSPro) algorithms.AdaGrad is an optimization method that allows different step sizes for different features. The RMSProp update adjusts the Adagrad method with an attempt to reduce its aggressive, monotonically decreasing learning rate. ADAM is computationally efficient and needs little memory. Models performance is compared according to MAE and MSE. Table II shows best five forecasting results out of 432 results. *d* shows dropout number (0, 0.1, 0.2), *l* shows layer and number of neuron in related layer. Most successful one is first layer with 50 neuron, second layer with 15 neuron and 0.1 dropout value. Sometimes the two layer configuration seems to have better forecasting performance than three layer configurations.

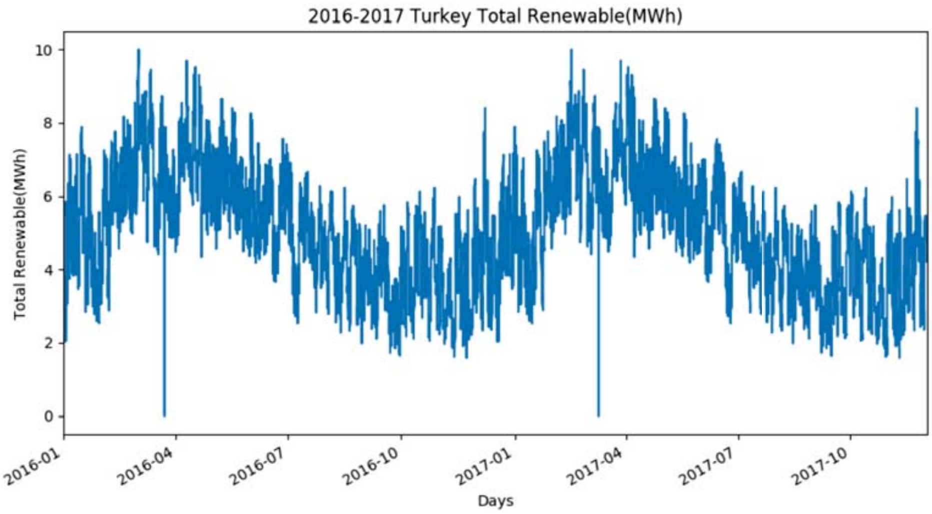

Fig. 4 2016-2017 Turkey Total Renewable Energy

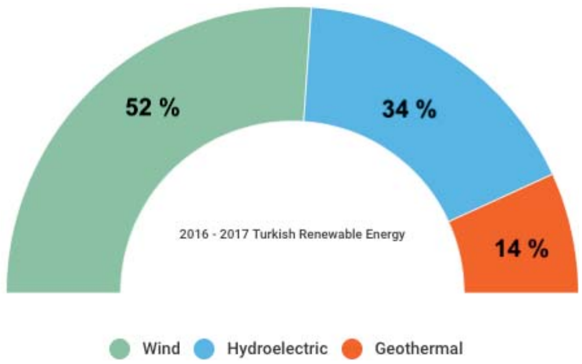

Fig. 5 Wind, Hydroelectric and Geothermal Energy

IV. Conclusion

Load forecasting is important for effective implementation of electricity energy polices. Load forecasting contributes to planning and policy formulations. Modeling load forecasting plays a vital role for policy makers. Underestimation of the load would lead to potential power outages, whereas oversestimation would lead to idle capacity that means wasted resources. There is need to the decision tools for load forecasting.

Renewable power forecasting is an important tool for decision making in energy markets. First step in the decision-making process is to choose an appropriate model. Autoregressive moving average, linear regressions, agent-based models, support vector machines, neural networks can be applied for load forecasting. Deep learning models are one of the electricity load forecasting model. Deep learning models can learn complex relationships in data. Second step is the test decision models forecasting accuracy. In this study, deep learning LSTM networks are used for renewable load forecasting. MAE and MSE are used to measure accuracy of the models.

This paper presented models for electricity load forecasting by using a deep neural networks in the Turkish electricity market. Experiments show that LSTM-based RNN is capable of forecasting accurately the electric load with a short-term forecasting horizon. In addition, medium-term and long-term forecasting should be carried out with deep learning to check its effectiveness.

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