The Eurasia Proceedings of Science, Technology, Engineering & Mathematics (EPSTEM)
ISSN: 2602-3199

The Eurasia Proceedings of Science, Technology, Engineering & Mathematics (EPSTEM), 2020

Volume 11, Pages 14-19

IConTES 2020: International Conference on Technology, Engineering and Science

Multivariate Short-term Load Forecasting Using Deep Learning Algorithms

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Abstract: Load forecasting is important in energy market. In fact electricity is a type of energy that cannot be stored, thus it is more important in electrical energy. The facilities need to balance between electricity generation and consumption by making plans. Computer-aided forecasting models are developed to reduce the effects of factors that disrupt this supply-demand balance. Generally, daily, weekly and monthly forecasts are made in demand forecast. In this study, hourly demand estimation is made. By using the past 24-hour consumption data and weather data such as temperature, humidity, wind speed and radiation in Konya, the next hour's consumption value was tried to forecast. Forecasting models were created using deep learning algorithms such as RNN, LSTM and GRU and the most successful model was determined by comparing the models.

Keywords: Load forecasting, Deep learning, Time series, Consumption of electricity, Short-term

Introduction

The need for electrical energy is increasing day by day due to reasons such as the development of industry and technology, the increase in population, factories and mechanization. It is necessary to make a planning that will ensure the supply-demand balance for increasing energy need. This plan is very important in order to prevent energy losses due to overestimation, to eliminate negative effects on costs and to prevent problems such as power cut that may occur due to underestimation. Therefore, load forecasting should be close to the actual value. It is possible to categorize the load forecast as short, medium and long term. Short-term load forecasting is in a period of a few minutes of a day. The medium-term load forecasting is in the time range of one day to one year, while the long-term load forecasting includes estimates that last more than one year (Nalbant et al., 2005).

There are different studies for short, medium- and long-term forecasting. Mori and Ogasawara (1993) developed recurrent neural network for short-term load forecasting using methods of time series and diffusion learning methods. In another study, attributes such as hours, days of week, holidays, past twenty-four hour of consumption and average consumption were used and RNN,LSTM and GRU methods were more successful than ARIMA and YSA methods (Tokgoz & Unal, 2018). Choi, Ryu and Kim (2018) presented a new model by combining ResNET and LSTM to perform one day ahead 15-minutes interval load forecasting. In this study, ResNET improved the model by providing that the neural network extracts the latent features of input historical load data. A new neural network model that integrates the hidden feature of CNN and LSTM is proposed to improve the forecasting accuracy (Tian et al., 2018) . Siddarameshwara et al. (2010) used Elman recurrent network with weather data such as average wind speed, speed, humidity, minimum and maximum temperature for short-term forecasting. There are many studies that used LSTM model for load forecasting (Jiang et al., 2018; Kong et al., 2019; Zheng et al., 2017).

In this study, three different forecasting models was created by using deep learning methods for short-term load forecasting and they were compared. Electricity consumption and weather data between 2016-2020 were used. In addition, this study is different from others in terms of regional and hourly. A multivariate model was created by using weather data such as temperature, wind speed and radiation in addition to past twenty-four hour of

- Selection and peer-review under responsibility of the Organizing Committee of the Conference

consumption and the next hour's consumption was tried to be forecasted. When the results were compared, it was seen that the forecasting value is close to the actual value.

Method

Data Preparation

In this study, 30758 hourly data of Konya province between 2016 and 2020 is used. In addition, eight features is used namely temperature, relative humidity, wind speed, wind direction, cloud cover, radiation, precipitation and consumption. 70% of data for training, 15% for validation and 15% for test is divided. Some preprocessing was implemented to data before the training of the models. Also, standardization was implemented input and output of the models using formula given in Equation-1 to give for the model to give more accurate results.

$$z = \frac{x_i - \mu}{\sigma} \qquad (1)$$

The hourly change of consumption data of Konya province between 2016-2020 is shown in Figure-1.

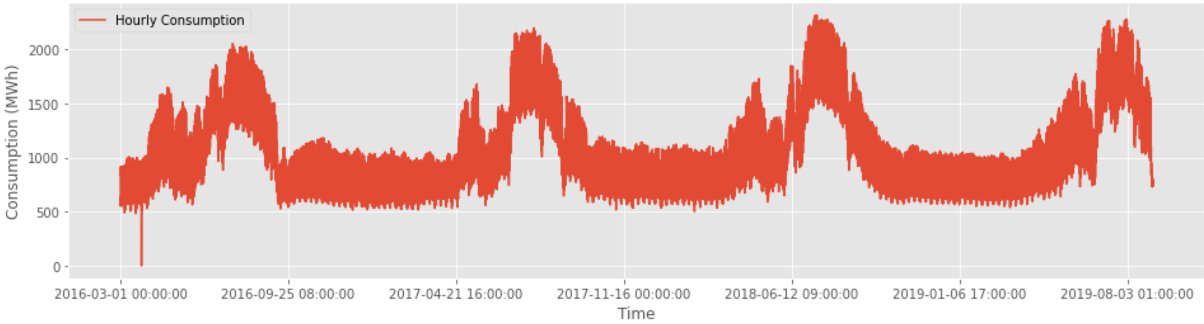
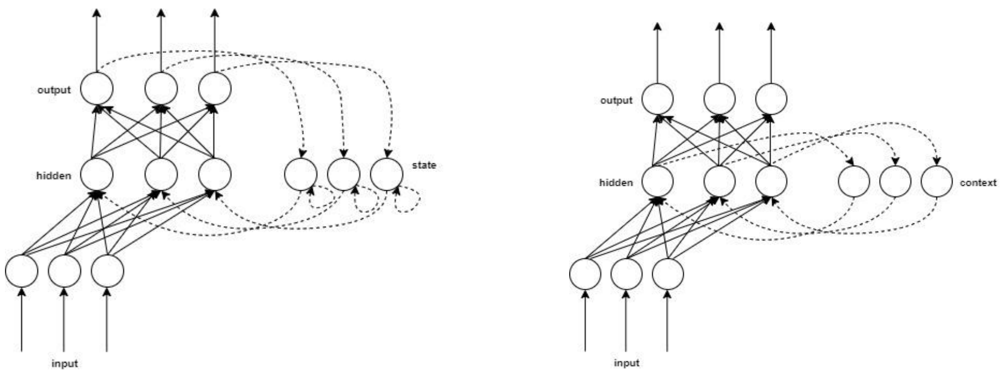


Figure 1. Electricity consumption data graph

Recurrent Neural Network (RNN)

Recurrent neural network is a neural network which allows hidden states to use previous outputs. Inputs are independents from each other in standard neural network. In other words, previous data is not important for next data. But previous data is needed for problems such as time series that contains sequence pattern. In this case, RNN which keep in memory to information from previous data was discovered.

Figure-1 shows the architecture of Jordan and Elman networks, which are among first recurrent network. Jordan networks are similar to MPL with input, output and hidden layers (Figure 2a). It has state units in addition to MLPs. This state units transport the data from output layer to hidden layer in the next iteration. Also, these units have a connection to themselves. on the other hand, Elman networks have a context layer. While input of this context layer derived from outputs of hidden layers, its output sent back to input of hidden layers (Figure 2b).



(a) (b)

Figure 2. (a) Architecture of Jordan recurrent network (b) Architecture of Elman recurrent network

The memory structure of the RNN can be understood by looking at the opened version of the RNN in Figure-3. When each new input comes, hidden layer information of the previous input in addition to this new input is also given to the model. Thus, previous input is kept in memory.

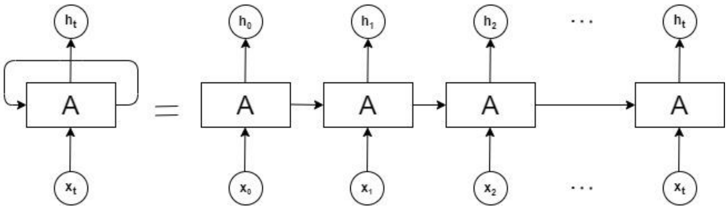
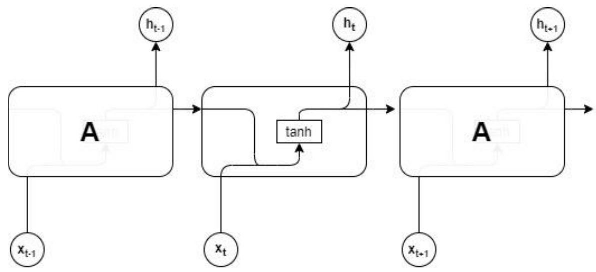


Figure 3. Opened version of RNN

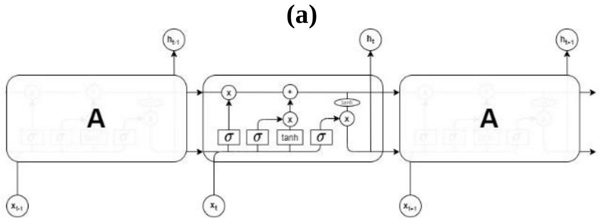
Long Short-Term Memory (LSTM)

Past data is used while training the model in the RNN. However, as the time interval increases, it becomes difficult for RNN to use historical data and effects of the input on the output is decreases due to gradient vanishing problem. To solve this problem, LSTM which is special type of RNN and can learn long-term dependencies has developed. LSTMs is similar to the architecture of RNN in the Figure-3. However, while recurrent module in RNNs contains single layer as shown Figure 4a, the structure of this module in LSTMs is different and includes four layers (Figure 4b).

LSTMs consist of three gates as input, output and forget gate.



(a)



(b)

Figure 4. (a) Internal structure of RNN (b) Internal structure of LSTM

Gated Recurrent Units (GRU)

The Gated Recurrent Unit can be viewed as simplification of the LSTM, which does not use explicit cell states. There are some differences between the two models. The LSTM directly controls the amount of information changed in the hidden state using separate forget and output gates. On the other hand, a GRU uses a single reset gate to achieve the same goal. Just as the LSTM uses input, output, and forget gates to decide how much of the information from the previous time-stamp to carry over to the next step, the GRU uses the update and the reset gates (Aggarwal, 2018). The update gate preserves the previous data for current state. However, reset gate is the gate that define whether combined to data in current and previous state.

Results and Discussion

The result of the three model is applied were evaluated with performance metrics such as MSE, RMSE, MAE and R square. While high R square value indicates that relationship of forecasting is good, low values of other metrics indicate that the performance of the model is high.

In this study, consumption of the next hour is tried to be forecasted by the 24-hour historical data of the province of Konya for 2016-2020. Timesteps value is selected as 24 to give for input 24-hour historical data. Two hidden layer that has 50 and 45 neurons respectively is used. It was seen that the increase in the number of layers and neurons negatively affected the results, so these values were kept to a minimum. In addition, the Grid Search algorithm is used for learning rate selection and the best value is $1e^{-3}$. As a result, models were created with 8 inputs and 1 output parameters. Deep learning algorithms is stochastic. In other words, these models have randomness such as initializing to random weights and model can produce different results. For this reason, training of models repeats many times for robust results and is used summary statistics of results to compare models. The results of each iteration are shown in Table-1. Then, the average error values of these experiments are calculated, and the best performing algorithm is determined. The values in Table-2 show that the best performing algorithm is RNN.

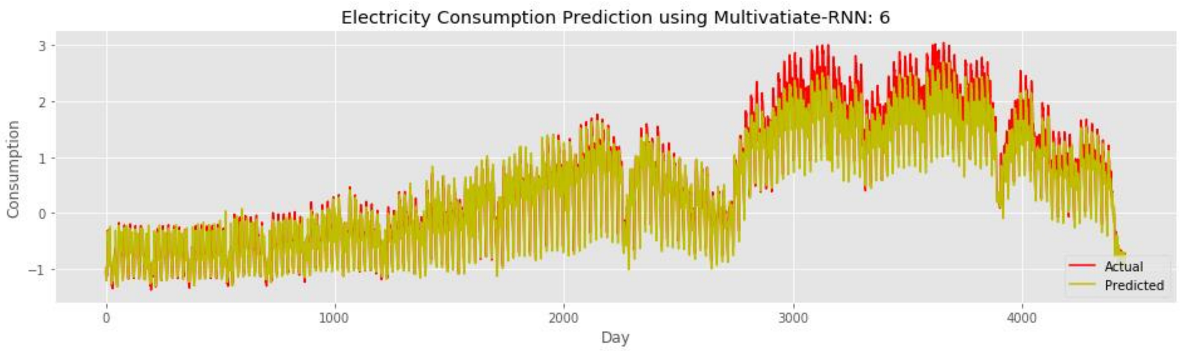
Table 1. 10 iteration results of models

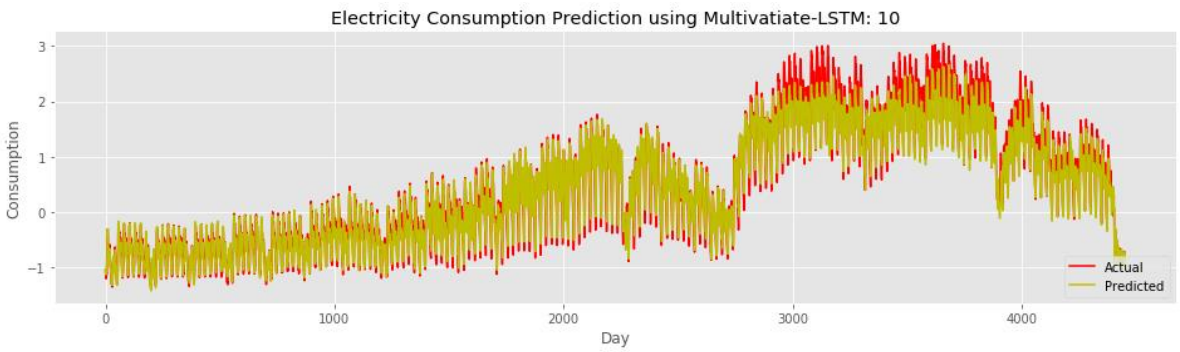
	MSE			RMSE			MAE			R^2		
	RNN	LSTM	GRU	RNN	LSTM	GRU	RNN	LSTM	GRU	RNN	LSTM	GRU
1	0,0472	0.0749	0,0512	0,2173	0.2737	0,2264	0,1637	0,1906	0,1645	0,9598	0,9363	0,9564
2	0,0492	0.0538	0,0968	0,2218	0.2319	0,3112	0,1650	0,1766	0,2346	0,9582	0,9542	0,9176
3	0,0419	0.0897	0,0502	0,2047	0.2995	0,2240	0,1583	0,2220	0,1697	0,9644	0,9237	0,9573
4	0,0570	0.1132	0,0843	0,2388	0.3365	0,2904	0,1791	0,2554	0,2092	0,9515	0,9037	0,9283
5	0,0569	0.0562	0,0625	0,2385	0.2371	0,2499	0,1827	0,1811	0,1871	0,9516	0,9522	0,9469
6	0,0406	0.0573	0,0595	0,2015	0.2393	0,2439	0,1493	0,1812	0,1861	0,9655	0,9513	0,9494
7	0,0510	0.0455	0,0618	0,2259	0.2135	0,2486	0,1691	0,1535	0,1835	0,9566	0,9612	0,9474
8	0,0537	0.1129	0,0535	0,2318	0.3360	0,2312	0,1729	0,2505	0,1666	0,9543	0,9040	0,9545
9	0,0541	0.0841	0,0699	0,2325	0.2900	0,2643	0,1790	0,2189	0,1994	0,9540	0,9285	0,9406
10	0,0599	0.0405	0,0657	0,2447	0.2014	0,2564	0,1847	0,1510	0,1884	0,9491	0,9655	0,9441

Table 2. Average performance of multivariate models

Model	MSE	RMSE	MAE	R^2
RNN	0.0512	0.2258	0.1704	0.9565
LSTM	0.0729	0.2659	0.1981	0.9380
GRU	0.0655	0.2546	0.1889	0.9443

Actual and predicted values of test data are shown in Figure-5. When these graphs are examined, it is seen that the trend of all three models approaches the actual values.





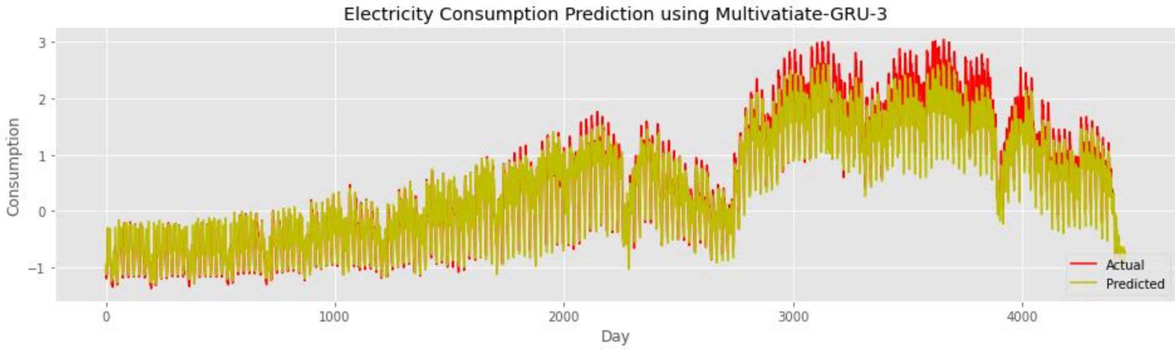


Figure 5. Actual and predicted values of model results

In order to analyze the estimation results in more detail, a certain section is taken from the model results and shown in Figure-6. In some parts, the GRU algorithm overestimates the true value, while LSTM algorithm underestimates it slightly. Despite these, it was seen that the closest estimate to the actual values was made in RNN model.

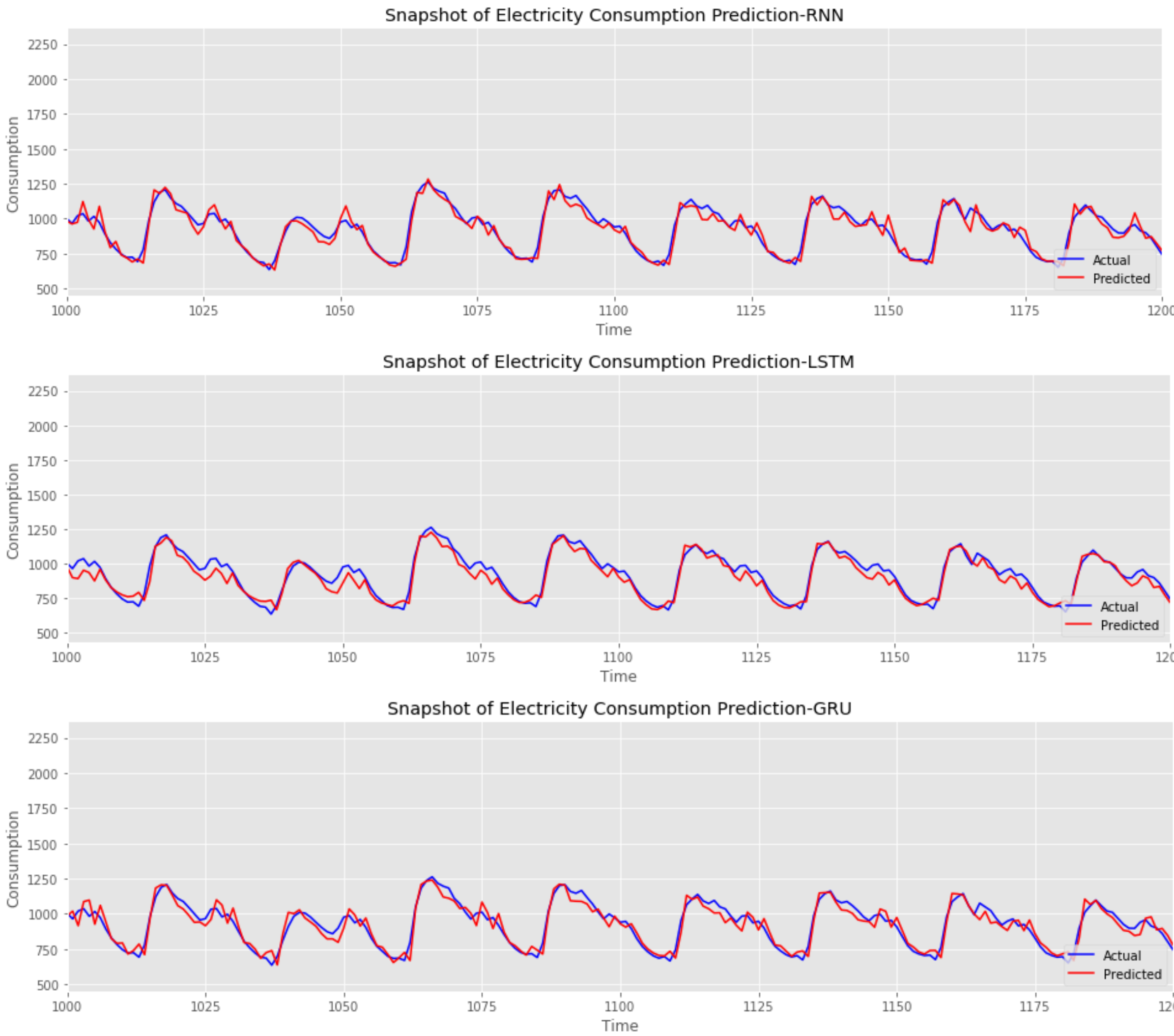


Figure 6. Snapshot of actual and predicted values of model results

Conclusion

The planning of consumption forecast is importance in energy sector. For this reason, the estimation should be as close to the truth. Negative effects that occur due to overestimation and underestimation should be prevented by maintaining the balance supply and demand. Computer aided applications have been developed in order to minimize the errors originated from human and sensor data in the estimation data. The aim of this study is to estimate hourly consumption by using three different deep learning models.

In general, estimation models have been developed with time series methods using only consumption data. However, other factors affecting consumption are ignored. In this study, weather data were used in addition to consumption data for the training of the network and multivariate prediction models were created. Also, the addition of historical data has increased the accuracy rates by directly affecting the learning process of the models. In order to reduce the stochasticity of deep learning models and to reach more precise results, the models were run multiple times and their statistical averages. According to these results, the most successful algorithms are listed as RNN, GRU and LSTM.

Acknowledgements

We would like to thank Meram Elektrik Perakende Satış A.Ş (MEPAŞ) for providing consumption and weather data used in models designed in this study.

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