Forecasting of Energy Consumption and Production Using Recurrent Neural Networks

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Abstract. *Energy forecasting for both consumption and production is a challenging task as it involves many variable factors. It is necessary to calculate the actual production of energy and its consumption as it is very beneficial in maintaining demand and supply. The reliability and smooth functioning of any electrical system are dependent on this management. In this article, the Recurrent Neural Network (RNN) based algorithm is used for energy forecasting. The algorithm is used for making three days ahead prediction of energy for both generation and consumption in Estonia. A comparison is also made between our proposed algorithm and the forecasting algorithm used by Estonian energy regulatory authority. The results of both algorithms indicate that our proposed algorithm has lower Root Mean Square Error (RMSE) and is giving better forecasting.*

Keywords

Forecasting, Energy Consumption, Energy Generation, Machine Learning, Neural Networks.

1. Introduction

The worldwide usage of energy is increasing each year. The regulators are trying to lower the carbon footprint and overall cost of energy by increasing the number of renewable energy resources [1]. However, the growing demand for energy needs to be predicted timely for the better planning of energy production and distribution [2]. This can help any operator in bridging the gap between demand and supply, proper demand-side management, system reliability, and maintaining power quality [3].

The generation of energy depends on many factors like the number of energy sources, type of energy source and in case of renewable energy production, it also depends on the weather conditions. Similarly, the consumption depends on day and night time, weather season, type of loads, residential and industrial usage and many other factors. These problems make it a challenging to meet the ever-growing energy demands [4]. An accurate energy forecast can help in better management of the electrical power system [5]. Nowadays, machine learning algorithms are popular in energy forecasting [6]. They can be used for the forecasting of load [7], energy production and consumption [8], solar and wind energy forecasting [9], etc. This forecasting can be up to one day (short-term) [10], a few days or weeks (medium-term) and months ahead (long-term) [11].

The motivation behind this research is to make accurate energy forecasting models. Due to the increased usage of renewable energy resources and their uncertainty related to natural conditions [12], these models have become of extreme importance. In the near future, more and more residential buildings will become microgrids and distributed energy sources [13]. These future smart girds require scalability and flexibility. This forecasting will also help in better operation and control of these future smart grids.

In this article, the Recurrent Neural Network (RNN) based forecasting algorithm is proposed for the energy forecasting. A dataset of Estonian energy production and consumption is used to create this forecasting model. This model is then used for making short-term and medium-term predictions. The simulation results of this algorithm are then compared with the results of the Estonian Energy Regulatory Authority (ELERING)'s forecasting algorithm. The results show that the proposed model outperforms the ELERING's algorithm based on the Root Mean Square Error (RMSE) value. The main contribution of this research is highlighted as follows:

- The forecasting model is developed for energy production and consumption in Estonia.
- The proposed forecasting algorithm gives 3-day ahead predictions.
- RNN based forecasting algorithm offers more accurate forecasting as compared to ELERING's forecasting.

The remainder of the article is organized as follows: the survey of related work is given in Sec. 2. Section 3. contains detailed information about neural networks and the proposed algorithm. Section 4. is regarding the case study of Estonian energy forecasting and finally, Sec. 5. presents the conclusion of this article.

2. Literature Review

Forecasting models are used to predict the availability or utilization of energy. This helps in better management of resources and also has great economic and environmental impact. Most of the forecasting models used today are based on machine learning. Some statistical models [14] are also available. Although they are not widely used as they lack accuracy [15].

These forecasting models are used in the load prediction of residential buildings [16], transportation loads [17] and overall energy consumption of a city, province or country. A hybrid model for long-term power consumption forecasting was introduced in [18]. This model was based on conditional interference trees and linear regression. This model outperformed random forests and conditional interference tree algorithms. Two deep RNN based forecasting models are proposed in [19] for medium to long term load prediction. These models are used in commercial and residential buildings in Salt Lake City and Austin, US. The RNN model gave a lower mean error as compared to the conventional neural networks model. Similar studies have been made for Chinese provinces of Hebei [20] and Hunan [21] for long term load forecasting.

In [22], short term load forecasting was created using the Stack Multi-Learning Ensemble (SMLE) network. The experimental results and analysis showed that it outperforms the classical models. The machine learning based model is also used in the prediction of future energy demand in [23]. A smart energy usage mechanism is proposed based on electricity tariff and occupancy profile. The results showed a 25 % cost reduction.

A fuzzy time series model for monthly energy consumption has been proposed in [24]. In [25], a Markov chain-based model is made for the forecasting of energy demand. Three deep learning based forecasting methods were evaluated in [2]. The algorithms are Fully Connected, Convolutional Neural Networks (CNN) and RNN. The results indicate that RNN is best in terms of absolute and relative errors. The Long Short-Term Memory (LSTM) shows the best results in terms of lowest errors.

It is clear from all the above research that machine learning based algorithms are good for energy forecasting if a sufficient amount of data is available. The accuracy of the dataset is also very important.

3. Recurrent Neural Networks

RNN is a type of deep learning algorithm that uses a layered architecture inspired by the human brain. This is one of the most used methods nowadays. CNN are another type of deep learning. The major difference between RNN and CNN is that CNN only uses the current input while RNN uses current and previous inputs as well. These techniques are also known as Artificial Neural Networks (ANN).

LSTM [26] algorithm is based on RNN. It is an iteration-based method that stores information, which is used later for computations. It also stores information for an extended period, which makes it different from other neural networks. This makes LSTM a relatively short version of neural networks.

This RNN algorithm-based LSTM algorithm is suitable for regression-based problems and forecasting. In this algorithm, an LSTM network is trained for sequence-to-sequence regression. Then, its response is shifted by one value in each time step. The input sequence predicts a value for every step. Figure 1 depicts the block diagram of this algorithm [27] and [28].

The LSTM layer consists of hidden states and cells, the current state of the cell is used for computations and it is updated after each time interval. The information in each cell is either added or deleted after each time interval. The data flow of a cell is shown in

Fig. 2. It also shows how the information is updated or removed from the cells [27].

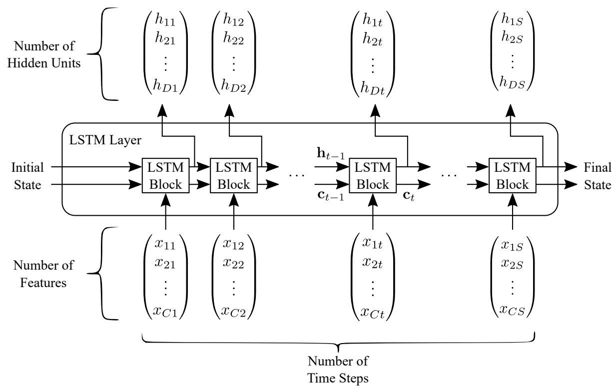

Fig. 1: The Architecture of LSTM Algorithm.

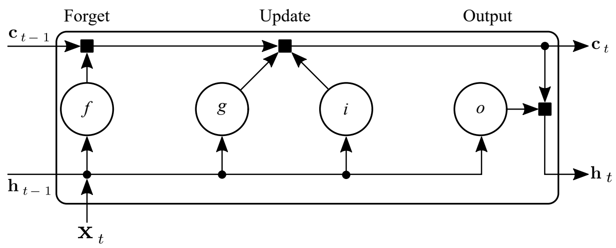

Fig. 2: The data flow in a cell.

4. Case Study of Estonia

Estonia is a Baltic country that lays in the northeastern part of Europe. Most of its energy is generated from fossil fuel while a significant portion is generated by renewable energy sources. The pie chart in Fig. 3 shows the proportion of renewable and non-renewable energy. In 2019, 78 % of the energy was generated from the fossil fuels in Estonia [29].

The actual values of energy consumed and produced in Estonia are shown in Fig. 4 [29]. The average energy consumption in Estonia is around 1000 MWh with a peak value of around 1500 MWh is winter. The average value of energy produced is around 600 MWh and a peak of around 2000 MWh. Most of the time, the amount of energy produced is lower than the energy consumption. The energy gap can vary from 200 MWh to 600 MWh. To overcome this vast gap, Estonia imports electricity from Finland and Latvia [29].

As Estonia is importing energy most of the time, the forecasting of domestic energy production and consumption becomes very significant. The ELERING uses a forecasting algorithm for the day-ahead prediction of energy consumption and generation. The results of this forecasting give them an estimate of future energy usage and import amount requirements. The actual consumption and predicted consumption of energy for July 2019 is shown in Fig. 5. The gap between actual and predicted values can reach around 100 MWh. Similarly, Fig. 6 shows the actual energy produced and the predicted energy production by the forecasting algorithm for the same month. It can be seen from the graphs that the predicted values are much higher than the actual values. The average gap is below 100 MWh, but it can go up to a peak value of 300 MWh.

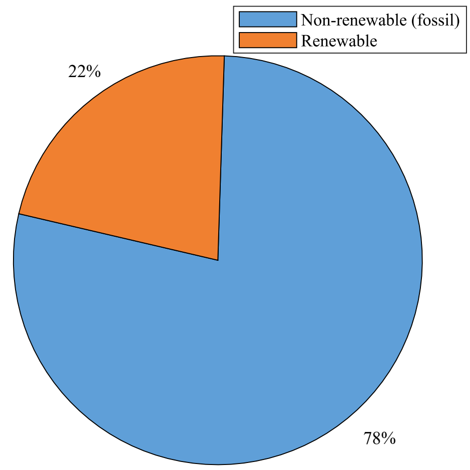

Fig. 3: Distribution of renewable and non-renewbale energy in Estonia.

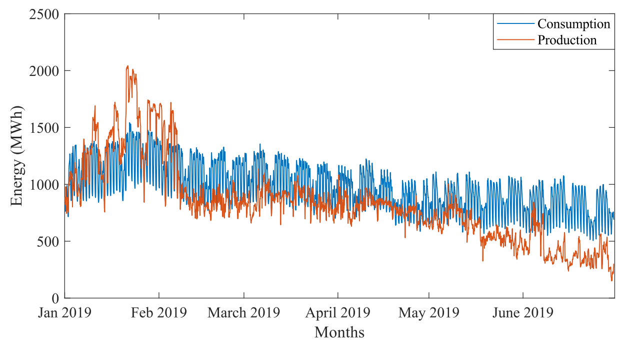

Fig. 4: Energy generation and consumption in Estonia.

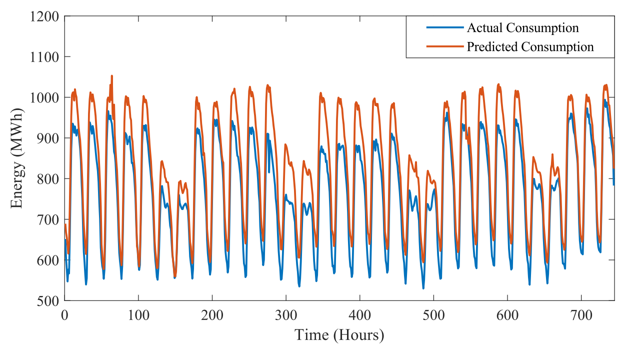

Fig. 5: Actual energy consumption vs predicted consumption.

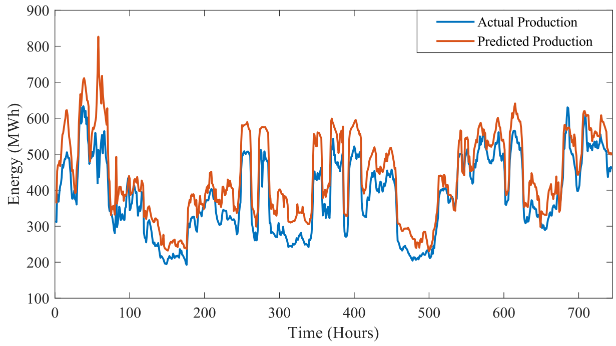

Fig. 6: Actual energy production vs predicted production.

As explained earlier, the forecasting algorithm introduced herein is based on RNN. The dataset of one-year energy generation and consumption of Estonia is being used to develop the forecasting model.

The dataset is divided into training, validation, and testing data. The RNN model is trained on the first 80 % of the data sequence, the model is validated on the subsequent 10 % data sequence, and the testing is performed on the last 10 %. To avoid divergence of training and for a better fit of the data, the training data sequence is converted into a standard zero mean and unit variance form. The testing data is also standardized similarly (using the same parameters) at the prediction time. The predictors and responses are generated for required multistep ahead prediction. The LSTM regression network is defined using 200 hidden units in the LSTM layer. The selection of hidden units is based on the trial and error method. The units are varied in the range of 20–300 and the model fits best for 200 hidden units and no improvement in the error is observed over 200. The input and output of the model are one; therefore, the number of features for the input layer is 1. Similarly, the number of responses for the fully connected layer is also selected to 1. The solver for the training is '*adam*' that is trained for 250 epochs. To avoid the gradient exploding problem, the threshold for the gradient is selected to 1. Moreover, the standard initial learning rate of 0.005 is selected. However, the learning rate is dropped by a factor of 0.1 after every 50. For multistep ahead prediction, the prediction function predicts time steps one at a time and then update the network state at each prediction. For each new prediction, the previous prediction is used as an input to the function.

Then a three-day ahead forecasting of energy consumption is made using this model. The forecasted results are depicted in Fig. 7.

The forecasting model used by ELERING only predicts the day-ahead forecast for energy consumption. Our forecasting algorithm is predicting the energy consumption values for three days ahead. Figure 8 is depicting the testing results of the forecasting algorithm. The predicted results are very close to the actual values. This result means lower values of RMSE. Figure 9 shows the RMSE values of the forecasting.

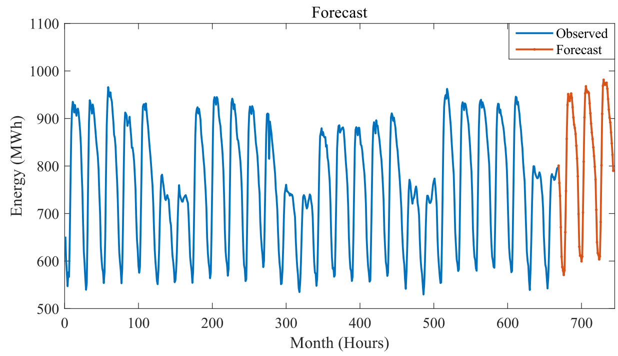

Fig. 7: Forecast of energy consumption.

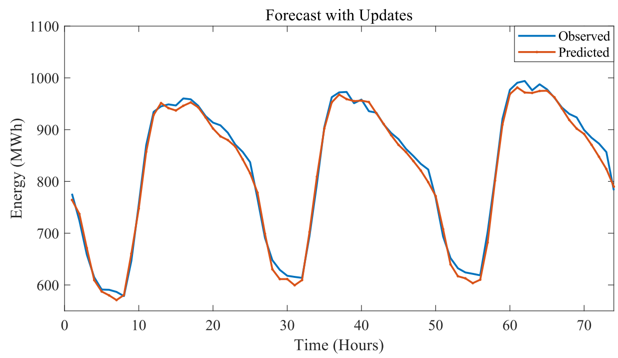

Fig. 8: Predictions for energy consumption.

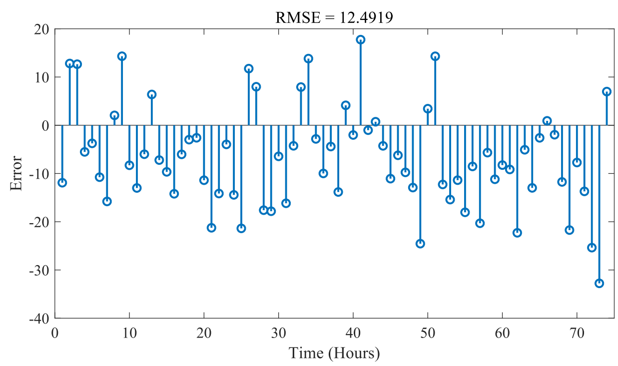

Fig. 9: RMSE values for the prediction.

These predictions have an RMSE value of around 12, while the maximum value of RMSE is 33. This shows the accuracy of this algorithm. The RMSE value for Elering's algorithm for day-ahead prediction is around 40. This results in the variations between actual and predicted values. Now, the same algorithm is used to make the forecasting of energy production. The three days ahead forecasting results for energy production are depicted in Fig. 10. The forecasting model is predicting values for the last three days (72 hours) of July 2019.

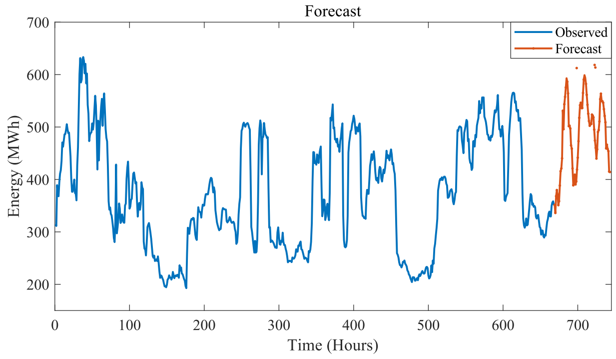

Fig. 10: Forecast of energy production.

Figure 11 shows the comparison of actual energy generated values and the predicted values by the forecasting algorithm. It can be seen that the forecasting values are almost following the same pattern of the original values. However, there are still some variations. These variations are caused by very rapid changes in energy generation values. These changes are due to the presence of a significant amount of renewable energy sources (wind energy) as described earlier (see Fig. 3). The prediction graph is still much closer to the original value thus resulting in a reasonable RMSE value. Figure 12 is showing the RMSE values for the predicted production.

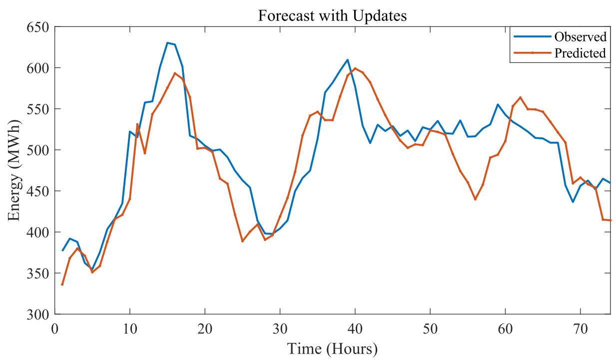

Fig. 11: Predictions for energy production.

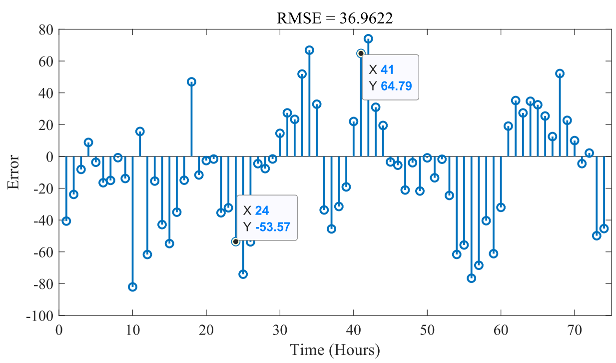

Fig. 12: RMSE values for energy production.

The RMSE value of ELERING's algorithm for energy production is around 47. However, the RMSE value of our algorithm is around 37, which is still considerably less. Finally, Fig. 13 shows the comparison of actual energy consumption, Elering's predicted energy consumption and our algorithm's predicted energy consumption values for one day. Similarly, the same comparison for energy production values is shown in Fig. 14.

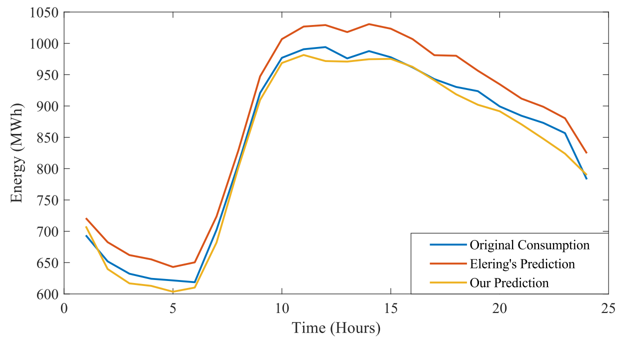

Fig. 13: Prediction of energy consumption for both algorithms.

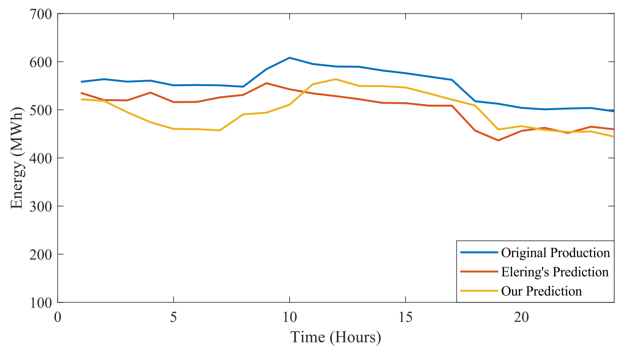

Fig. 14: Prediction of energy production for both algorithms.

5. Conclusion

The balance between energy consumption and generation has always been a challenging task. Thus, making their accurate forecasting a very important task. In future smart grids, this forecasting will play a very significant role. It has major effects on the technical, operational and economic aspects of the power grid. Especially, for those countries that have a gap between energy production and consumption, and they import electricity from neighboring countries.

In this article, a deep learning algorithm is used for the short term and medium-term prediction of energy production and consumption in Estonia. The data of one-year Estonian energy generation and consumption was used to build this model. The forecasting algorithm is developed on RNN based LSTM. The algorithm is giving forecasting for both energy consumption and production for three days ahead period. Besides, a comparison is made between the results of the Estonian energy regulator's forecasting algorithm that gives only one day-ahead prediction. In comparison, the proposed algorithm gives prediction for up to three days ahead. The RMSE values for both algorithms forecasting are given in Tab. 1. The RMSE value of RNN based algorithm for energy consumption forecasting is less than one-third. Similarly, for energy production, it is 21 % better than the other algorithm's results. Based on these results it can be concluded that the RNN based forecasting algorithm is more suitable for this type of forecasting.

Tab. 1: Comparison of RMSE values.

Algorithm	Energy consumption	Energy production
ELERING	40.309	47.345
LSTM	12.492	36.962

These results are very helpful in balancing energy production and demand. In addition, due to the higher accuracy of these results, they can offer more economical aspects and better management of the grid. As Estonia is mostly buying electricity for other countries, the regulators can have an early indication that how much energy will be required for the next 72 hours and from where they can get it at a cheaper price.

In future research, this model can be enhanced to provide forecasting for weeks and months ahead. This will require an extended dataset of energy consumption and production. In addition, a multi-variable complex model may be introduced to cater to the stochastic behaviors of the generation of energy from renewable sources. This will make the results of energy production forecasting more accurate.

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