# Peak Load Forecasting Based on Long Short Term Memory

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**Submission date:** 15-Oct-2022 10:10PM (UTC+0800)

**Submission ID:** 1926007160

File name: Peak\_Load\_Forecasting\_Based\_on\_Long\_Short\_Term\_Memory.pdf (1.11M)

Word count: 2100 Character count: 11450

### 2019 International Conference on Informatics, Multimedia, Cyber and Information System (ICIMCIS)

# Peak Load Forecasting Based on Long Short Term Memory

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Abstract—Electricity load forecasting is a very imperative issue not only in the power industry but also one of the factors to expand the economic efficiency of power and integral to the plan and execution of various vital. In this case, we use a machine learning approach, exclusively, Long Short Term Memory (LSTM) for predicting future the peak load based on historical data which recorded from Sub-Station in Lhokseumawe, Indonesia. LSTM is capable of forecasting complex univariate electric load time series with strong no-stationarity. The result shows the effectiveness of LSTM and outperform traditional forecasting methods in the challenging peak load record problem.

Keywords—forecasting, peak load, LSTM, electricity, machine learning

#### I. INTRODUCTION

Electricity is not only currently the most important energy sector in the domestic sector and industry in Indonesia, but also is the key factor for living science. As we know, electricity plays a vital role in national economic and social development. The forecasting of power is of crucial importance for the development of the modern power system [1], [2]. The forecasting of the load from several minutes up to one week and a month into a future had been focused and helps utilities and energy providers deal with the challenges posed. Various load forecasting methods have been proposed by researchers over the years [3]-[10]. Some of the models had been used for load forecasting include support vector machine [8], [11]-[13], LSTM [1], [14]-[16], monte Carlo [1], [5], etc. In general result, by using the load data set and comparison with the existing model show that the proposed model can provide accurate load forecasting result and high generalization capability. In this study, the availability of electric energy especially in Lhoksuemawe, Aceh, Indonesia has become an inseparable part of human life. The time series of electric load which recorded form substation in Lhoksumawe, Indonesia for one year, 2017. In this paper, we propose that LSTM can adapt to learning the complexity of time series peak load data. The proposed model demonstrates more effective use of the parameter of each LSTM's layer to train the forecasting model efficiently. A machine learning techniques by using LSTM can predict the time series of peak load.

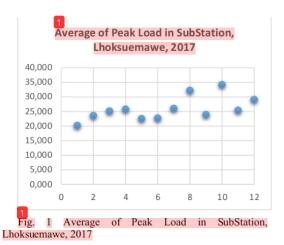
#### II. LITERATURE REVIEW

The peak load data forecasting is an essential process in the arrangement and task of electric utilities. According to the load forecasting techniques, there are many approaches to classified and predicted load data. The statically relationship between total load and weather condition as well as the day type influences by multiple regression analysis [17]. In 1995, [18] presented a hybrid approach using exponential smoothing to predict the future load. This model has been shown to compare favorably with conventional methods of load forecasting. The iteratively reweighted least-squares is one of the methods to identify the model order and parameter. The other methods had been developed by [17], [19], to keep track of changing load condition in adaptive load forecasting. The adaptive load forecasting used in the utility control system based on Kalman filter theory in regression analysis. LSTM a variation of deep Recurrent Neural Networks (RNN) primarily developed by [20]-[22] to allow the continuation of weights that are forward and back-propagated through layers. A different approach for peak load forecasting can be broadly classified as engineering methods in artificial intelligence (AI) methods. Diverse other approaches covering simple linear regression, multivariate linear regression, nonlinear regression and support vector machines (SVMs) were practical for electricity demand forecasting. Furthermore, we believe that adoption of AI methods in solving peak-load forecasting problems needs more maturity through increasing the number of works with different forecasting configuration. In this case, we propose an LSTM based model for predicting future the peak load based on historical data which recorded from Sub-Station in Lhokseumawe, Indonesia.

#### III. DATA AND METHODS

#### A. Data

The data used for this paper is recorded from Pusat Listrik Nasional (PLN) in Substation, Lhoksuewae, Aceh, Indonesia. The time series for one year in 2017. It includes a daily record of electricity peak load consumption.



#### B. Methods

The goal of this work is to predict future electricity peak load requirement based on the data available from 2017 using LSTM. The LSTM is compared in univariate time series prediction for the day ahead load forecasting. The LSTM is good in remembering information for a long time and fortunately, LSTM network a special form of RNN is capable of learning such scenarios [1], [14]–[16].

In Fig. 2 describe the proposed methodology process for forecasting LSTM as depicted. It is process can be seen as a framework of three processing components, explicitly, data preparation and processing component, the machine learning based on LSTM model and LSTM validation component.

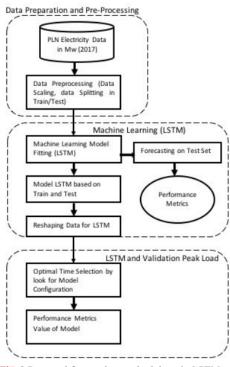


Fig. 2 Proposed forecasting methodology in LSTM

## 1 IV. RESULT AND DISCUSSION

As machine learning based on the LSTM model is sensitive to the scale of the inputs, the peak load data are normalized in the range [0,1] by using feature scaling. The peak load data is used for evaluating the accuracy of the proposed forecasting model not used in the training step.

The result of the data testing based on LSTM for monthly can show in Fig. 3. Plot of actual peak load data against the predicted value by the LSTM model for the average monthly, as medium term prediction.

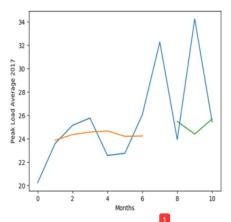


Fig. 3 Monthly electricity peak load prediction based on LSTM

It can be seen from the figure that the predicted peak load demand are not very close to the actual ones. The train score in this case 1.41 and test score 5.75 with approach 100. This condition causes the data set was processed by medium-term forecasting for a few weeks to a few months in 2017.

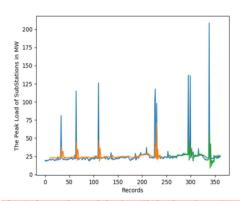


Fig. 4 Time series peak load prediction based on LSTM

In Fig.4 show the prediction based on the time series data in 2017. The predicted peak load demand has seen very close to the actual ones. Using LSTM indicate an impressive ability to approximate the actual data. The root means squared error (RMSE) for the training score is 12.71 RMSE, and Test Score 23.31 RMSE with 100 epoch. The time series of peak load

data split is a model selection methods inspired by validation suitable for time series case.

The method involves repeating the process of splitting the time series into train and test sets. The validation of result using simple train test split, multi-train test split and on various time horizon showed that LSTM based forecasting methods have lowe forecast errors in the challenging short daily to medium-term peak load forecasting as a univariate time series problem and thus the approach can be generalized to other peak load times series data.

#### V. CONCLUSION

In this paper, we have proposed a machine learning system for prediction future peak load demand based on historical peak load demand data without Meteorological data. The machine learning techniques are proving useful for electricity load forecasting. The goal system uses LSTM for constructing a model for peak load demand in Lhoksuemawe Area, Indonesia to be used prediction purpose. The LSTM based on the time series histories showed a good prediction performance for weekdays. In the future, intend to implement an incremental LSTM framework to periodically re-train the LSTM to adapt to any changes such as the increased peak load demand.

#### ACKNOWLEDGMENT

The authors acknowledge the support from the Universitas Malikussaleh, Lhoksumawes, and Universitas Sriwijaya. The authors also thank PLN, Lhoksumawe, Aceh, Indonesia for providing the data in this study.

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