Lightweight Multivariate LSTM for Industrial Power Prediction in Smart Grid

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***Abstract*—This paper proposes a lightweight multivariate long short-term memory (LSTM) look-back model to predict smart grid (SG) power consumption with an industrial approach. Since the power demand increases continuously and the previous studies use a complex architecture, a lightweight prediction that provides low loss and computing time is needed. We reduce the number of layers and utilize multivariate features to improve the prediction performances from previous research. Based on the simulation results, the proposed approach outperforms the existing approach in terms of prediction loss.**

***Index Terms*—Smart grid, lightweight prediction, long short-term memory(LSTM), multivariate look-back**

I. Introduction

Smart Grid (SG) is a new decentralized power management system that manages energy demand and supply stability. Rapid utilization of various industrial appliances leads to fluctuating power demand on the consumer's side. In order to anticipate those problems and keep the SG stable, a power prediction is mandatory.

The current trend of power consumption prediction uses various techniques to achieve better prediction result. Deep learning (DL) is the most popular approach in data science that capable of classifying modulation [1], action recognition [2] and other issues. The most popular DL algorithm to predict time series long short-term memory (LSTM). In [3], author utilize the multi-layer LSTM to predict energy load with temperature fuzzification and outperforms the other traditional algorithms. LSTM is implemented in [4] to predict missing sensor data with look-back method outperforms multi-layer perceptron (MLP). Another prediction of residential power energy consumption was conducted by exploiting the Bidirectional LSTM algorithm [5]. Most of the previous studies are done by a univariate dataset without any supportive feature.

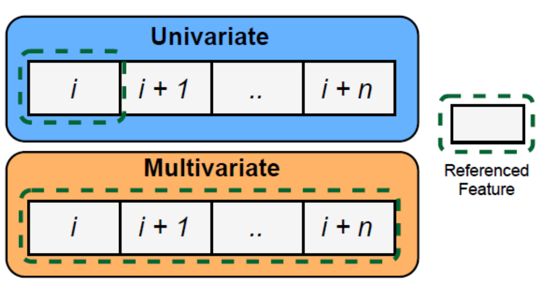

Fig. 1. Univariate and Multivariate dataset sampling

A lightweight DL-based technique to predict industrial power by evaluating multivariate features is proposed to address the mentioned problem. Based on Fig. 1, the difference between univariate and multivariate described. In univariate, one variable is used to predict the next sequence. On the contrary, the multivariate approach considers the multi-feature of the dataset to predict. The main contribution of this paper are listed as follows:

- A lightweight prediction model using multivariate LSTM by reducing the total number of hidden layers.
- The multi look-back approach is also applied to maximize the feature historical data.
- Compare univariate and multivariate features approach in terms of training loss and computing time to generate a single prediction data.

The paper structured as follows. Section II describes the previous studies in energy consumption prediction. Section III detailed the proposed system. Performance evaluation and conclusion in Section IV and V, respectively.

II. Related Works

Load forecasting research has been conducted before to achieve higher prediction accuracy. However, usually complex system model will affect the increment of computing time. The author in [3] proposed multi-layer LSTM to predict the energy load based on temperature fuzzification. Multi-layer represents a three-level stack of LSTM hidden layers. The results show that the LSTM outperforms the back-propagation (BP) neural network and the support vector machine (SVM) algorithm in terms of root mean squared error (RMSE).

Implementation of LSTM to predict missing sensors data described in [4]. LSTM is used to indicate the sensor value in case of the sensor fails to provide new data. The author used the multi-look back technique to provide better results with high complexity model. The result shows that the multi-look back LSTM outperforms the seasonal autoregressive integrated moving average (ARIMAX) and MLP algorithm.

Bidirectional LSTM also becomes an approach to resolve these issues. In [5] a multi-layer bidirectional LSTM (M-BDLSTM) to predict the residential power energy consumption is proposed. The performance evaluation shows that the M-BDLSTM outperforms the other algorithms regarding error loss function. The main focus of those studies mentioned before is accuracy, without considering the computing time.

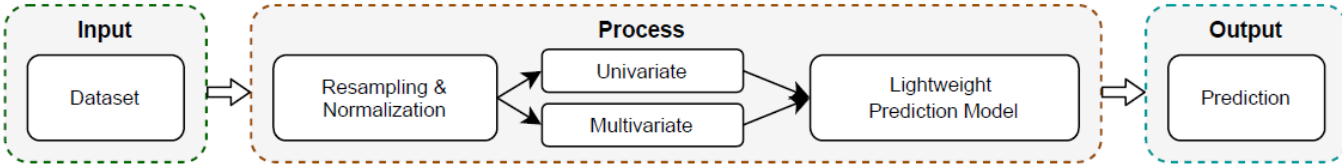

Fig. 2. The architecture of proposed system design

III. Proposed System Design

The current usage of LSTM utilizes a high number of layers which affect the prediction performances. This paper proposes a lightweight LSTM by reducing the size of hidden layers and adapting multivariate features fed into the system. A total 32 number of hidden layers with a dropout layer and a dense layer are used. Finally, adam is applied as an optimizer to the last dense layer with mean squared error, is used as a loss function, and the model trained in 50 epochs. Fig. 2 illustrates that the proposed model is implemented with univariate and multivariate data. In terms of look-back, we implement one and three levels of look-back with six variables and 18 variables, respectively.

IV. Performance Evaluation

This paper simulates the proposed system model on top of Google Colaboratory using Keras library with NVIDIA GTX 1050 and 2GB VRAM. The consistent number of layers and dataset were maintained for objective comparison.

Fig. 3 shows the training loss of various algorithms that we have compared. The multivariate LSTM three-level look-back (mLSTM-lb3) outperforms the other algorithms with lowest loss is around 0.00362, where for uLSTM-lb1, mLSTM-lb1, uLSTM-lb3, mBiLSTM, and mMLSTM is 0.00398, 0.00387, 0.00393, 0.00385, 0.00383 respectively. The computing time of all algorithms compared with multivariate LSTM are shown in Fig. 4. It can be seen that our proposed algorithm, lightweight mLSTM-lb3 outperforms the other algorithm with 0.0175 ms to produce single prediction.

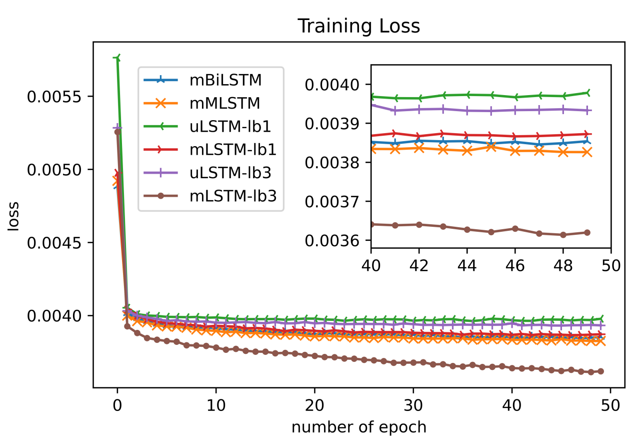

Fig. 3. Loss comparison among all algorithms

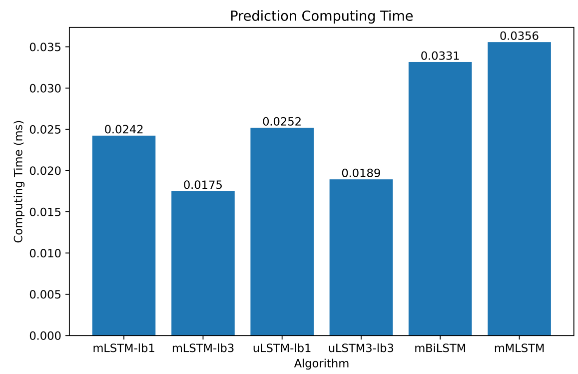

Fig. 4. Computing time of all algorithms

V. Conclusion

This paper proposed a lightweight multivariate LSTM look-back model to predict the power consumption with industrial approach. We apply the low number of layers with dropout and dense as output. The primary purpose of this research was to obtain lower loss with a lightweight DL model that could be applied easily. Based on the result, the proposed model outperforms the other algorithms.

Acknowledgment

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References

[1] A. P. Hermawan, R. R. Ginanjar, D. Kim, and J. Lee, “CNN-based Automatic Modulation Classification for Beyond 5G Communications,” IEEE Communications Letters, vol. 24, no. 5, pp. 1038–1041, 2020.

[2] T. Huynh-The, C. Hua, and D. Kim, “Encoding Pose Features to Images with Data Augmentation for 3-D Action Recognition,” IEEE Transactions on Industrial Informatics, vol. 16, no. 5, pp. 3100–3111, May 2020.

[3] R. Zhichao, C. Chao, D. Yingying, Z. Wentao, W. Jun and Z. Ruixiao, “Short-Term Load Forecasting of Multi-Layer LSTM Neural Network considering Temperature Fuzzification,” 2020 IEEE Sustainable Power and Energy Conference (iSPEC), 2020, pp. 2398-2404.

[4] A. P. Hermawan, D. -S. Kim and J. -M. Lee, “Sensor Failure Recovery using Multi Look-back LSTM Algorithm in Industrial Internet of Things,” 2020 25th IEEE International Conference on Emerging Technologies and Factory Automation (ETFA), 2020, pp. 1363-1366.

[5] F. U. M. Ullah, A. Ullah, I. U. Haq, S. Rho and S. W. Baik, “Short-Term Prediction of Residential Power Energy Consumption via CNN and Multi-Layer Bi-Directional LSTM Networks,” in IEEE Access, vol. 8, pp. 123369-123380, 2020.