Deep Learning Application in Power System with a Case Study on Solar Irradiation Forecasting

Aslam Muhammad
Dept. of Electrical Engineering
Myongji University
Yongin, South Korea
aslammju@gmail.com

Jae Myoung Lee
Dept. of Computer Engineering
Myongji University
Yongin, South Korea
ljm93inkr@gmail.com

Sug Won Hong
Dept. of Computer Engineering
Myongji University
Yongin, South Korea
swhong@mju.ac.kr

Seung Jae Lee
Dept. of Electrical Engineering
Myongji University
Yongin, South Korea
sjlee@mju.ac.kr

Eui Hyang Lee
Next-Generation Power Center
Myongji University
Yongin, South Korea
nptcmju111@gmail.com

***Abstract*— Power systems are developing day by day due to the inclusion of latest digital technologies. Due to the increasing complexities in power systems and collection of high volume of data, Deep Learning (DL) techniques are becoming most suitable technologies for its future development and success. Due to high performance computing with decreased computational cost, availability of huge amount of data, and better algorithms, DL has entered into its new developmental stage. This article introduces state of the art of application of Deep Learning in power systems, and presents a novel case study on the solar irradiance forecasting required for PV generation. The case study is prediction of hourly, daily and total solar irradiation forecasting for a year ahead using Long-Short Term Memory (LSTM). Year ahead data is important from the point of view of installation planning and market.**

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

I. Introduction

DL is becoming the hottest topic in almost all fields of technology due to its surprising results. Presently, DL has shown its extraordinary ability in many areas, such as image and speech recognition and natural language processing [1]. The effectiveness of DL is due to the availability of huge amount of data and high performance computing. Like other fields it is also getting attraction in power systems. DL is a subfield of machine learning, made from Artificial Neural Network (ANN). Different architectures of DL are: Feed Forward Networks (FFN), Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN) and Long-short Term Memory (LSTM). Out of these, CNN and RNN are most famous. CNN work good in dealing with spatial data or classification on the other hand RNN has shown effectiveness in time series analysis and prediction. As far as frameworks are concerned, main DL frameworks are TensorFlow, Caffe, Cognitive Toolkit, Torch and Theano, etc. This article presents an overview on the application of DL in power systems and presents a novel case study. Section I is introduction about DL, Section II introduces some of application of DL in power systems giving state of the art, Section III introduces different architecture of DL applied in power systems and Section IV gives a case study of hourly and daily solar irradiance forecasting for a year ahead and total irradiation for year ahead. Yearly ahead solar irradiation forecasting using DL is novel to the best knowledge of authors. Section V gives conclusion.

II. Application of DL in Power Systems

With the advance in power systems, high penetration of renewable energies and active participation of consumers results in operation of power systems in more complex way. Conventional power system analysis and control techniques depend mainly on physical and numerical modeling. These methods are not that much capable of solving recent power systems issues. At the same time, wide deployment of Advanced Metering Infrastructure (AMI), Phasor Measuring Units (PMUs), Wide Area Monitoring System (WAMS), Sensors, weather departments and market provide huge amount of data. Therefore, DL is suitable technology for the future development and success in power systems. Many research works have been done recently on DL in power systems. Following are some brief state of the art of DL application in power systems.

A. Forecasting of Load

With the uncertainty in nature of customer, load forecasting has always been a challenge. In [2], FFN is used to improve the accuracy of load forecasting. Forecasting of demand for individual building is also becoming a hot topic as it helps to find out local demand response. Smart meters collected local data can be used for forecasting individual building by using DL. LSTM based model is used to predict one hour and one minute time step loads in [3]. DL is suitable for accurate load forecasting as it can deal with huge amount of data from smart meters, PMUs and other sources. Method of selecting number of parameters and hidden layers and their nodes are still an open question to be answer by the researchers.

B. Power System Restoration

Outages are occurred due to uncontrollable situations. In order to minimize negative impact of outages, deep FFN is trained to perform optimal actions during power system restoration. First, Restoration Model (RM) was developed to simulate system restoration. The RM was designed to handle any topological degradation of a system and enable interactive exploration of the actions required to bring the system back to an ideal state. Moreover, a cost function was developed in order to evaluate the quality of a given sequence of actions in the context of restoration cost. Using the RM as a simulation environment and the cost function as an evaluation measure, a dataset of optimal power system state-to-action pairs was created using a genetic algorithm (GA) by optimizing restoration action sequences on the Icelandic transmission system. The FFN was trained via supervised learning using the created data, achieving 75% test accuracy on optimal decisions. The FFN agent was further tested in a comparison to the GA and operators of the Icelandic system. Results show that the FFN is 3 orders of magnitude faster than GA at developing a restoration plan, and performs comparably to human operators on a simple test restoration scenario.

C. Demand and Response

Forecasting and finding energy flexibility on demand side is essential for applying demand response. In [4], DL is applied to identify the flexibility of loads and to provide references for demand response. In [5] RNN is used to classify consumers and outperformed traditional methods nearly reaching the accuracy of almost 100%.

D. Detection of Defect or Faulty Equipment

For reliable power operation it is important to detect faulty equipment. DL is applied to monitor states of three main components of power systems namely insulators, transformers and transmission lines. CNN has been used in [6] to get features of insulators and identify defects showing accuracy of 93%. Based on DL fault diagnosis method of power transformer is proposed. Large unlabeled data from oil chromatogram on-line monitoring devices and small labeled data from dissolved gas-in-oil analysis are used to train network. Test results showed the diagnosis performance is better than traditional methods.

E. Stability Assessment, Disturbance and Emergency Control

In order to ensure reliability stability assessment, disturbance control and emergency control are very important. In [7], DL architectures like Multilayer Perceptron (MLP), Deep Belief Network (DBN) and CNN are used to perform automatic disturbance classification by using measurement from several PMUs. CNN showed high accuracy as compared to others in classification. Similarly DBN is used for transient stability assessment. DBN map the original feature space to representation space, in which stable cases can be linearly separated from unstable cases. DL model has also been used to support emergency management system.

F. Cyber Security

Communication system added to power systems provides efficient monitoring and control. However there is also risk of vulnerability to malicious attacks. False data injection (FDI) is a huge threat to power systems security. In [8], DL based method to detect FDI and power theft is proposed. Similarly, [9] used DL to investigate and detect data corruption by analyzing real-time measurement from PMUs.

G. Renewable Energy Generation Forecasting

LSTM and MLP are used for predicting solar and wind power generation. In [10]-[11] auto-encoder and LSTM are used for forecasting PV-generation outperforming all traditional techniques. DL methods are increasingly applying to generation forecasting due to availability of huge data from weather departments.

H. Power System Fault Diagnosis

In [12] application of deep learning neural network for power systems fault diagnosis is proposed. Data is extracted from power system dispatching department and preprocessed before training in the deep learning network. Then, processed data is put into auto-encoders and hidden features are observed in different dimensions so that can preliminarily judge about fault. Afterwards, trained stacked auto-encoders (SAE) is used to initialize and train a deep learning neural network (DLNN). The classifier is the last part of the network to reflect the types and possibility of diagnosis. The result of simulation proves the feasibility of the approach.

III. Deep Learning Architectures

DL has different architectures. To know best architecture is not easy as, some architecture is made for specific purposes and might not perform well on all tasks. Following sections present a description of the most important Deep Learning Frameworks and their applications in power systems.

A. Multilayer Perceptron (MLP): a Feed Forward Neural Network (FNN)

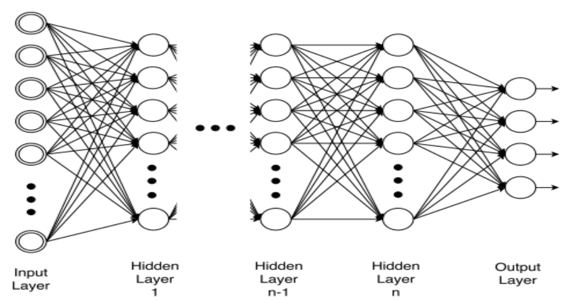


Figure 1. An example of MLP (FNN)

Multilayer Perceptron (MLP) a type of FFN as shown in Figure 1, which is a most basic DL architecture. In power systems, application of ANNs in general, and MLPs in particular, is wide and not a novelty: for instance, definition of protection schemes for transmission lines, determining location

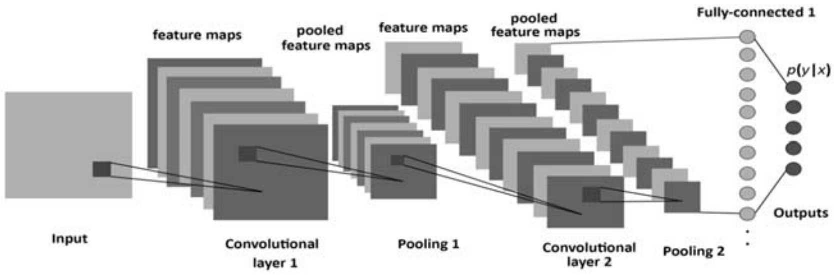


Figure 2. A convolutioanl neural network

of the fault with ANNs, transformer fault diagnosis , on-line voltage stability monitoring, forecasting problems of load, wind power and photovoltaic production.

B. Convolutional Neural Network (CNN)

CNN consists of multiple two-layer FFNs that adopt the mathematical convolution operation in order to transform low-level maps with local features into several high-level maps with global features. The pooling layer implements a max-pooling effect or average pooling effect, which is a form of non-linear down-sampling. The input is divided into a set of non-overlapping rectangles, outputting the maximum/average (pooling) of each sub-region. The pooling layer objective is to progressively reduce the spatial size of the representation, decrease the number of parameters and consequent amount of computational effort, and control overfitting issues. CNN architecture is shown in Figure 2.

There are several applications of CNNs in power systems. CNN is employed for power line insulators classification from aerial images. They are also implemented in insulator condition inspection. Uncertainties in wind power data can be effectively learnt for probabilistic wind power forecasting. High variability and volatility of wind power data is soothed by the employment of a hybrid Wavelet Transform, CNN and ensemble technique. CNN showed great efficiency to extract nonlinear and stochastic nature of each wind power frequency.

C. Recurrent Neural Network (RNN)

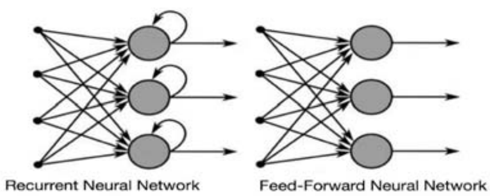


Figure 3. Recurrent Neural Network (RNN) compared with FFN

Recurrent Neural Networks (RNNs) are recent algorithm for sequential data and among others used by Apples Siri and Googles Voice Search. This is because it is the first algorithm that remembers its input, due to an internal memory, which makes it perfectly suited for Machine Learning problems that involve sequential data. They use previous time-step output as input in current time-step. A comparison of RNN to FFN is shown in Figure 3.

There are issues of vanishing gradient and exploding gradient with RNN, which are solved by extended form of RNN called Long-Short Term Memory (LSTM). LSTM's enable RNN's to remember their inputs over a long period of time. LSTM-RNN are applied in power systems mostly in time series forecasting like load forecasting, demand response and renewable power generation forecasting because of their ability to solve temporal data problems.

IV. Case Study

A. The Case: Solar Irradiation Forecasting

Due to increasing demand of renewable energy, research on renewable energy is increasing day by day. In order to estimate renewable energy capacity, ESS capacity, ESS operation simulation in design engineering and market benefits, it is necessary to predict the amount of generation and load before system installation. Total power generation of one year is required in order to estimate capacity for designing. It is necessary to predict the hourly and daily power generation for one year as well as the total power generation for one year in order to estimate the optimum capacity considering the operation of PV and ESS in systems like microgrid. Also, it is necessary to accurately predict the amount of solar radiation that have a huge influence on the prediction of PV power generation. The case study was done to predict year ahead hourly, daily and total solar irradiation.

B. Simulation and Results

The inputs for LSTM neural network are real-time solar radiation data of Seoul Korea from 2001 to 2017 obtain from Korea Meteorological Administration (KMA). In LSTM neural

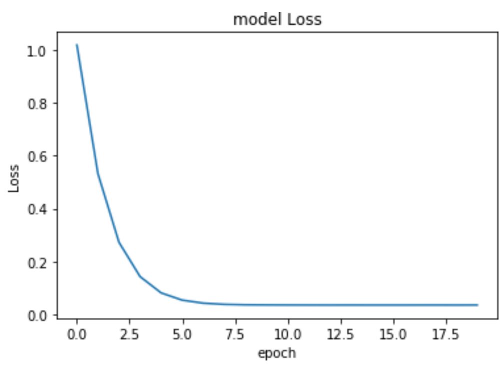


Figure 4. Loss value in LSTM model

network, we used the single input, two hidden layers, and one output layer. The data from 2001 to 2016 are used for training the model and data of 2017 is predicted and compared with the actual data. Inside the neural network model, final output layer is activated with linear regression function. The model was implemented in Python with Anaconda Jupiter notebook [13] with Keras and Tensorflow at back-end.

Loss value vs number of epochs obtained from the LSTM model is shown in Figure 4. From the figure we can see the loss value is smoothly decreased as the number of epochs increased. After the completion of the training, the model

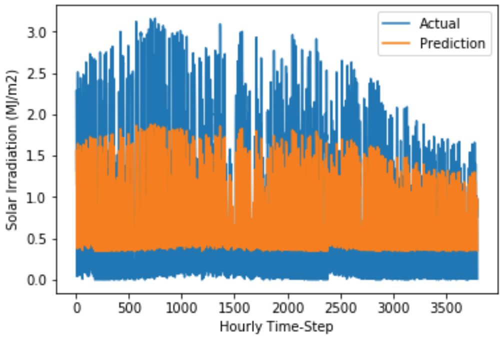
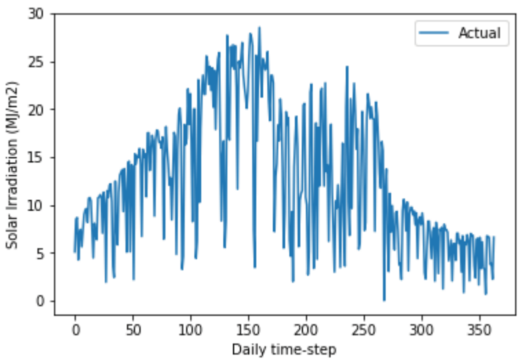
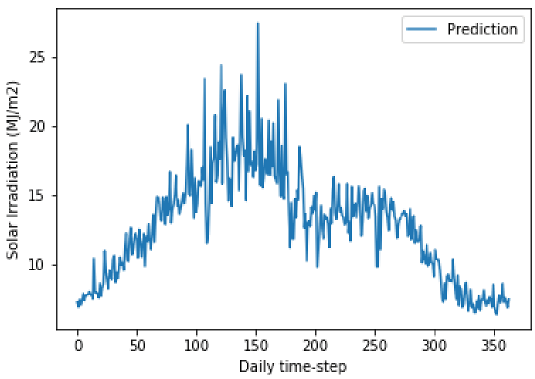


Figure 5. Comparison of hourly actual vs predicted data



(a)



(b)

Figure 6. Comparison of daily(a) actual vs (b)predicted data

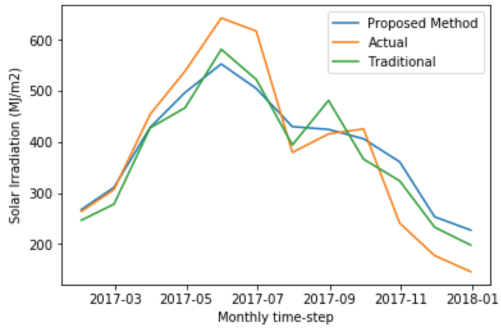


Figure 7. Comparison of actual, predicted data and traditional method

predicts long-term radiation. Figure 5 and Figure 6 shows the comparison of year ahead hourly and daily prediction vs actual value of 2017. Mean Squared Error (MSE) of 10.4 % is achieved in hourly prediction. Figure 7 shows comparison of actual, proposed method and traditional method [14].

TABLE I compares actual, predicted and traditional method [14] total irradiation for one year ahead. From comparison with actual data it can be observed that the proposed method predicted data is similar to the actual data while traditional method has more difference showing the effectiveness of the proposed method.

TABLE I. TOTAL YEARLY RADIATION FOR 2017

Year	Actual (MJ/m^2)	Proposed (MJ/m^2)	Traditional (MJ/m^2)
2017	4607.9	4663.3	4519.2
2016	4516.2	4576.5	4624.3
2015	4637.2	4562.6	4545.3

V. CONCLUSION

DL Deep Learning (DL) is one of the hottest topics for researchers in almost all field of technology due to the availability of huge amount of data and high performance computing. DL is also being implemented in power systems like in Load/Demand Forecasting, Demand Response, Power System Analysis and Control, Cyber Security, Power System Restoration, Fault Diagnosis and Renewable Energy Generation Forecasting. In this paper first overview of application of DL in power systems is given. Then most famous DL architectures adopted in power systems have been discussed. FFN is used in regression problems. CNN is used in classification problems like insulation fault detection and RNN-LSTM has been implemented successfully in time series problems like load forecasting. Finally a case study for the application of DL in power systems is done. Yearly ahead hourly, daily and total solar irradiation forecasting is implemented. Yearly ahead solar irradiation forecasting is required for PV generation which can be used in installation planning.

ACKNOWLEDGMENT

This work was supported by "Human Resources Program in Energy Technology" of the Korea Institute of Energy Technology Evaluation and Planning (KETEP), granted financial resource from the Ministry of Trade, Industry & Energy, Republic of Korea (No. 20174030201790), and by Korea Electric Power Corporation. (Grant number:R18XA01).

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