Study Committee C2

Power System Operation and Control

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Deep Learning Application for Power Generation Forecasting of VRE in Thailand

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Motivation

- Power networks are experiencing high penetration of variable renewable energy (VRE) resources which disrupt the traditional paradigm of one-way power flow, changing from centralized generation to distributed generation across the country.
- The nature of VRE is unpredictable and intermittent resources. The output of VRE varies depending on several meteorological conditions such as wind speed, solar irradiation, temperature, relative humidity. This poses many challenges for system operators in terms of operation planning and unit commitment scheduling. The renewable energy market is expected to grow rapidly, as a result of a significant drop in technology cost.
- VRE could bring both benefits and harms to the power networks. In order to optimize utilization of VRE, a reliable forecasting tool is essential.
- For the last decade, a variety of forecasting techniques and algorithms have been proposed and developed to improve the forecasting accuracy of power generation from VRE, including physical methods, statistical methods and artificial intelligence-based methods. Unarguably, renewable power forecasting has become crucial for power system operational planning to maintain reliability and quality of power networks.

Methodology

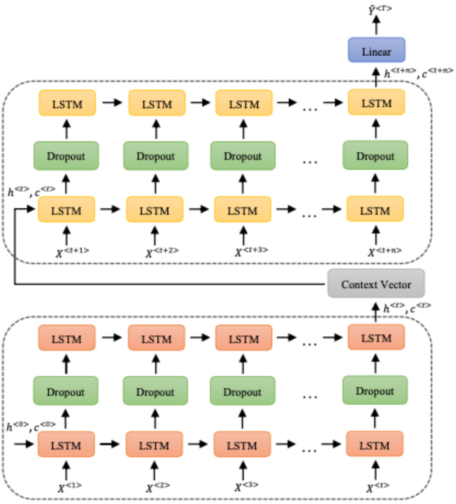

Figure 1. Proposed model architecture

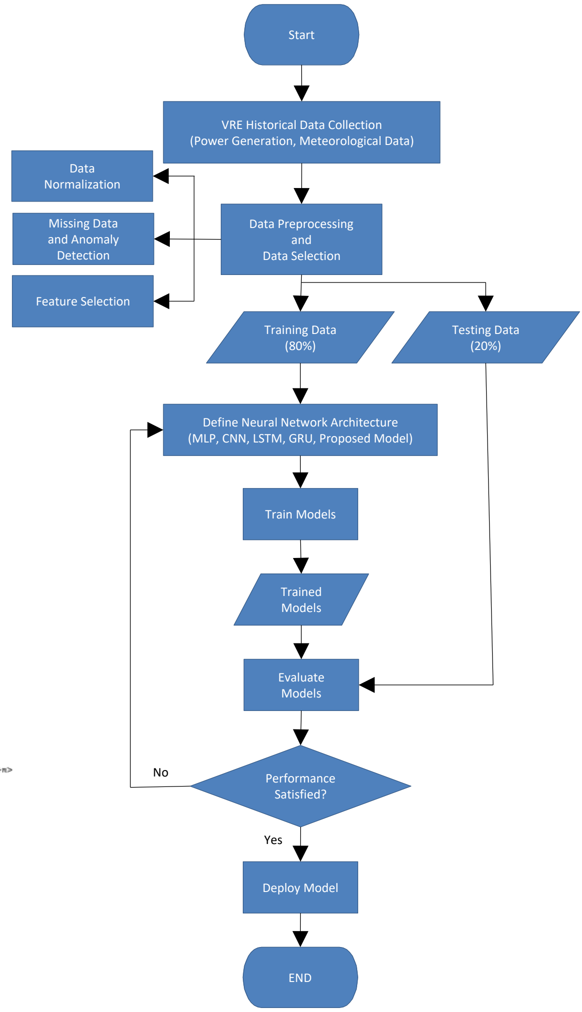

Figure 2. Workflow of VRE model development

Deep Learning Application for Power Generation Forecasting of VRE in Thailand

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Objects of investigation

Solar power plant with capacity of 55 MW located at 15°2´N, 100°53´E and wind power plant with capacity of 80 MW located at 15°36´N, 101°32´E were selected to verify the performance between the proposed model and the standard neural networks for VRE power forecasting. Both power plant data contains the historical power generation and meteorological data are half-hourly and span 3-year period between July 01, 2018 and August 01, 2020 accounting for 36,624 measurements. Data preprocessing and feature selection were performed and split into training (80%) and testing (20%) sets.

Table I. Correlation coefficient and value range of meteorological data of solar power plant

Variables	Value range	Correlation coefficient
Global horizontal irradiance (W/m^2)	0 - 1,063.46	0.83
Ambient temperature (°C)	9.49 - 39.47	0.38
Cloud cover index	0 - 1	0.71
Wind speed at 10 meters (m/s)	0.04 - 10.07	0.34
Dew point (°C)	4.39 - 26.12	-0.01
Surface pressure (hPa)	988.96 - 1,011.78	0.04
Relative humidity (%)	13.89 - 99.62	-0.40

Table II. Correlation coefficient and value range of meteorological data of wind power plant

Variables	Value range	Correlation coefficient
Global horizontal irradiance (W/m^2)	0 - 1,072.20	-0.21
Ambient temperature (°C)	8.25 - 37.81	-0.16
Cloud cover index	0 - 1	-0.17
Wind speed at 10 meters (m/s)	0.08 - 9.72	0.47
Wind speed at hub height (m/s)	0.18 - 15.62	0.67
Dew point (°C)	1.30 - 25.87	0.07
Surface pressure (hPa)	958.24 - 981.06	-0.14
Relative humidity (%)	12.83 - 100	0.24

Simulation details

The time-series data were prepared for training the neural network models by choosing the input sequence as 96 timesteps or 48 hours and the output sequence as 12 timesteps or 6 hours. The architecture of each neural network model is given below:

- MLP model has 2 hidden layers with 128 units at each layer.
- CNN model has 2 convolutional layers with a filter of 128, kernel size of 3, stride of 1 and padding of 1 at each layer
- LSTM model has a 2-stacked bidirectional LSTM with 128 cells at each layer.
- GRU model has a 2-stacked bidirectional GRU with 128 cells at each layer.
- The proposed model has 2 parts: the encoding part is a 2-stacked bidirectional LSTM with 128 cells at each layer for historical data, the decoding part is a 2-stacked bidirectional LSTM with 128 cells at each layer for future meteorological data, and a linear layer with the output size of 12.

The output of each model was connected to fully-connected layer for the final output sequence. The fully-connected layer contained a total unit of 12 units, which are equal to forecasting timesteps. All neural network models used Rectified Linear Unit (ReLU) activation function in all layers except in the output layer. Adaptive Momentum Estimation (Adam), stochastic gradient-based optimization, was used to optimize and update the parameters (weights and bias) of each neural network model during backpropagation with learning rate of 0.001. MSE was used as loss function or cost function to compute model error. Each neural network model was trained for a total of 100 epochs.

Simulation results

The performance of the neural network models was evaluated on solar power plant at forecasting period from 10:00 to 15:00 on 14 July, 2020. The results revealed that the proposed model achieved the highest performance on solar power plant among other methods with MAE of 4.50 MW, RMSE of 5.37 MW and MBE of -0.90 MW, as can be seen in Table III. MLP model yielded the worst performance with MAE of 13.84 MW, RMSE of 15.54 MW and MBE of -13.8 MW among other neural network models, while LSTM, GRU and CNN models gave better result compared to MLP model.

Table III. The performance of different neural network models on solar power plant.

Method	Performance Criteria		
	MAE	RMSE	MBE
MLP	13.84	15.54	-13.8
LSTM	9.78	13.8	-7.10
GRU	8.24	9.67	-2.77
CNN	10.89	12.48	-10.89
Proposed model	4.50	5.37	-0.90

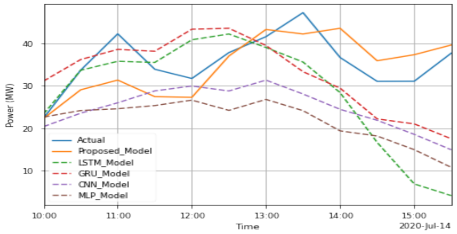

Figure 3. Simulation result on solar power plant

Study Committee C2

Power System Operation and Control

10986_2022

Deep Learning Application for Power Generation Forecasting of VRE in Thailand

continued

The performance of the neural network models was evaluated on wind power plant at forecasting period from 10:00 to 15:00 on 14 July, 2020. The proposed model is also able to outperform the other neural network models on wind power plant with MAE of 4.51 MW, RMSE of 5.48 MW and MBE of 0.45 MW, as can be seen in Table IV. MLP model shows the highest loss error scores compared to LSTM, GRU and CNN models.

Table IV. The performance of different neural network models on wind power plant.

Method	Performance Criteria		
	MAE	RMSE	MBE
MLP	8.62	10.04	-8.44
LSTM	6.17	7.73	-1.91
GRU	5.60	8.05	-3.03
CNN	4.63	6.45	-0.44
Proposed model	4.51	5.48	0.45

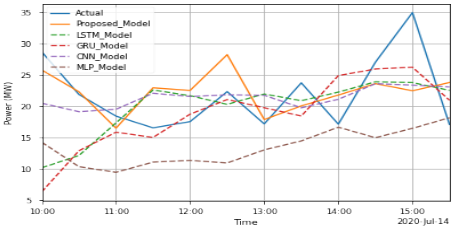

Figure 4. Simulation result on wind power plant

Discussion

- The mechanism of LSTM, GRU and CNN networks gain an advantage over MLP, in which LSTM and GRU network can extract temporal information and CNN network can extract spatial information from data. Such capabilities of RNN and CNN enable the models to capture fluctuating pattern of VRE power generation. Therefore, LSTM, GRU and CNN models yielded better accuracy than MLP model.
- LSTM, GRU and CNN models were inferior to the proposed model. Since LSTM, GRU, CNN and MLP models considered only historical data to forecast power generation.
- The proposed model not only considered the historical data but also future timesteps of meteorological data to forecast power generation. Therefore, the proposed model can forecast more accurately. This means that without future meteorological data, the model is unable to forecast power generation effectively.
- The potential forecast error of the neural network models may result from the unexpected defect or unreported maintenance of solar panels or wind turbines, which such phenomena are unknown in advance.

Conclusion

- This paper presents deep learning application for VRE power forecasting in Thailand by proposing deep neural network and comparing with standard deep neural networks which are MLP, CNN, LSTM and GRU.
- The proposed model understandably outperformed other models in terms of MAE, RMSE and MBE criteria among solar and wind power plants. This is because the proposed model also takes future timesteps of meteorological data into consideration.
- Deep neural networks are trained separately for each VRE power plant, because there are differences in meteorological and geographical characteristics of power plant location. As a result, the forecasting models of VRE power generation are relatively more effective and efficient.
- The results show that the proposed model is able to assist system operators to schedule generation effectively and efficiently.