Wind Forecast Using Extension of Conditional Generative Adversarial Networks with Geospatial-temporal data

Chiao-Ning Chuang[1]; Horng-Shing Lu[1]; Wen-Yi Chang[2]; Whey-Fone Tsai[2]
[1]Institute of Data Science and Engineering, National Chiao Tung University,
[2]National Center for High-Performance Computing, NARL

Introduction:

The development of offshore wind energy generation has been progressing at a rapid pace in recent years. In order to capture wind energy more efficiently and ensure lower maintenance costs of the wind turbine, we designed a deep learning model based on conditional GANs and aim to provide more accurate wind forecast results as the environmental information for the wind turbine yaw control system and then develop a reinforcement-learning-based method to optimize the control system to get the maximum wind energy to meet the needs in the near future.

Dataset

The dataset is collected since 2014 by Central Weather Bureau including the geospatial data of temperature, pressure, wind direction and wind speed. It is covered the region of domain 02 in Taiwan (see Fig.1) with the grid resolution of 5 km. Figure 2 shows that the raw data on the right side can be converted into the image with spatial information on the left side and we will use the converted data to develop an algorithm for wind forecast which it will be a spatiotemporal sequence forecasting problem.

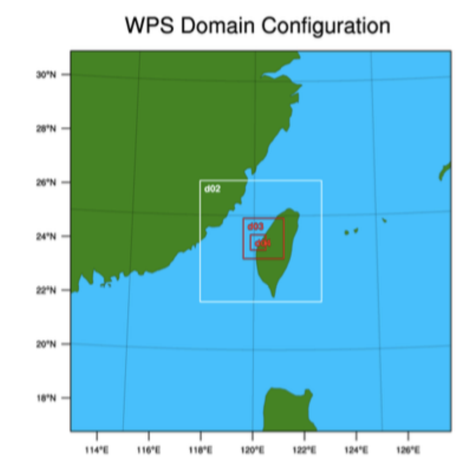


Figure 1: Model setup for the WRF simulations

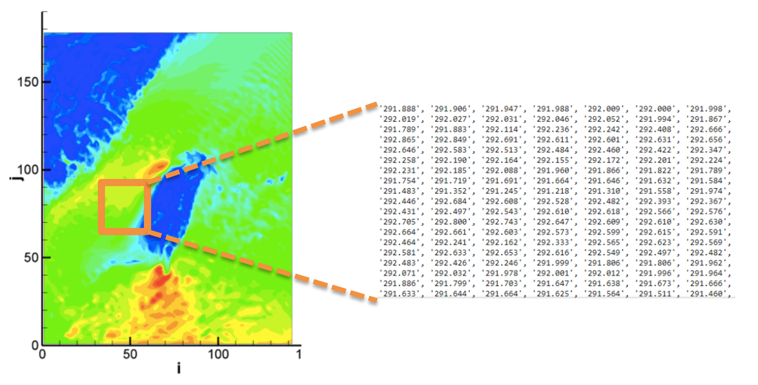


Figure 2: Conversion of raw grid data to an image

Methodology

A Convolutional LSTM (ConvLSTM) is a common deep learning generative model for video/multi-frames predictions. However, it cannot achieve good performance when it comes to complex dataset being trained. The conditional generative adversarial networks (cGANs) which are mostly used to implement image to image translation are our main structure of the model and we modified it to have a ConvLSTM model as the generator and Long-term Recurrent Convolutional Networks (LRCN) as the discriminator (see fig. 3) to allow cGANs to do spatiotemporal sequence predictions. With these two neural networks compete with each other, it can lead to a better-performing generator.

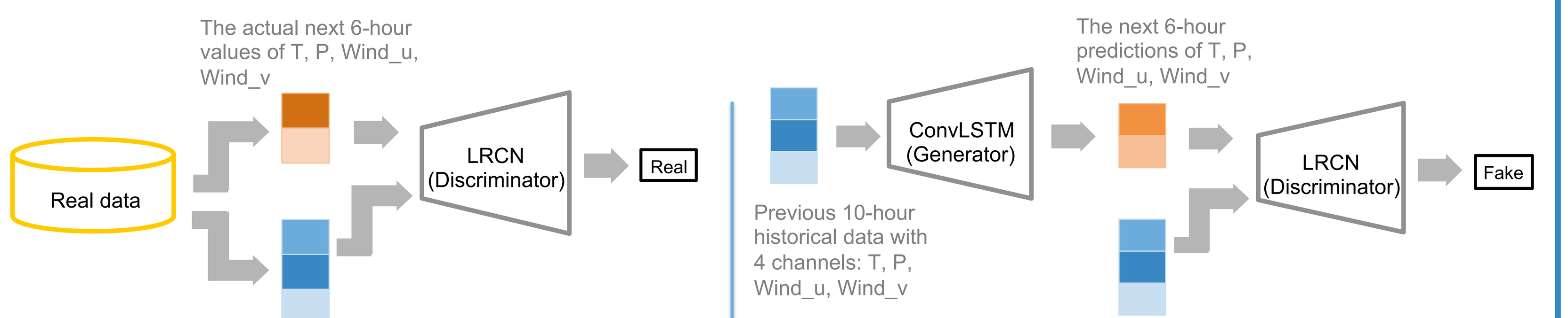
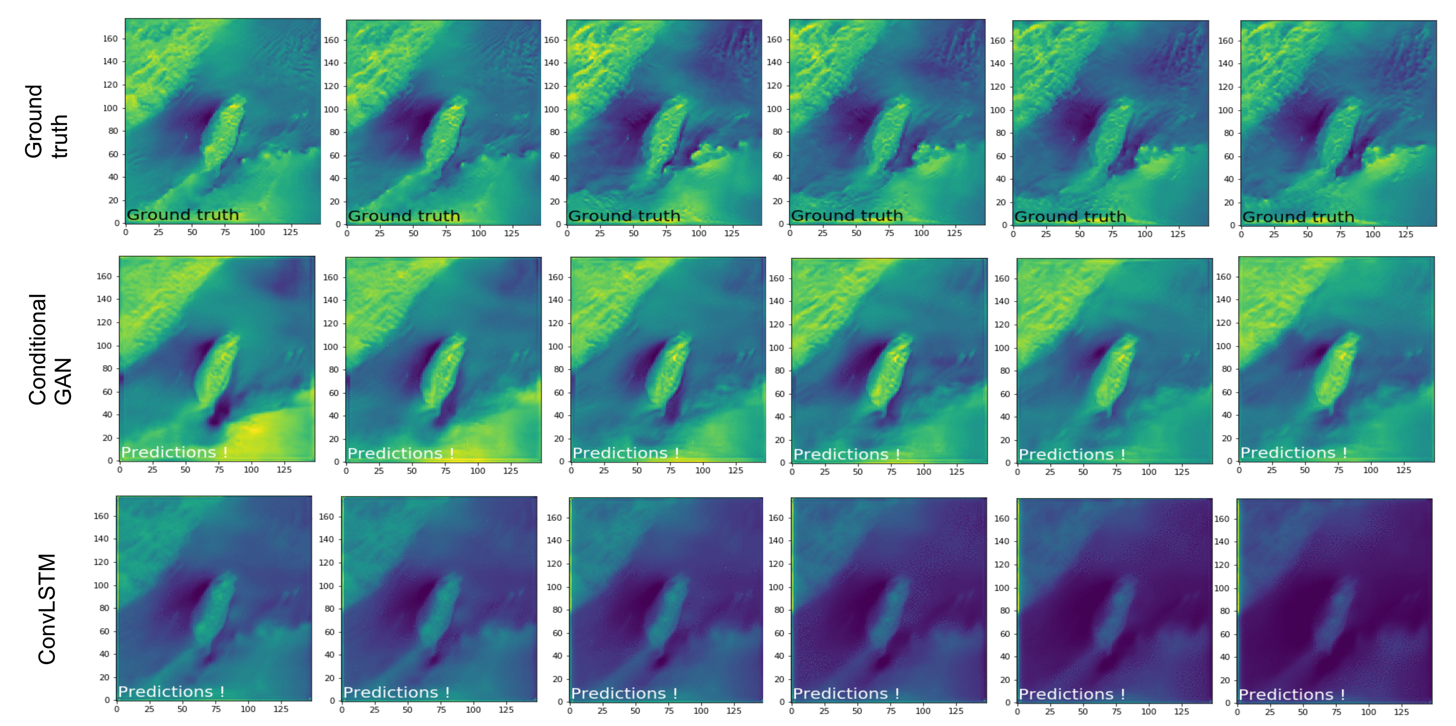


Figure 3: Conditional GAN model structure with ConvLSTM as the generator and LRCN as the discriminator

Experiments

In our experiment, the setup of model hyperparameters for both the generator of the modified cGAN and ConvLSTM are the same, and the models both predict 6 hours. The results from top to bottom: ground truth frames; prediction by cGAN; prediction by ConvLSTM.



Comparison of the average scores of two models over 6 prediction steps.

	ConvLSTM	cGAN
PSNR	22.67	27.02
SSIM	0.671	0.785
MSE	21.95	8.26
PSNR (local area)	25.10	27.66
SSIM (local area)	0.643	0.812
MSE (local area)	14.94	7.31

Image quality metrics:

1. PSNR (Peak Signal to Noise Ratio) $PSNR = 10 \cdot log_{10}\left(\frac{MAX_I^2}{MSE}\right)$
2. SSIM (Structure Similarity Index Measurement)

$$SSIM(x,y) = \frac{(2\mu_x\mu_y+c_1)(2\sigma_{xy}+c_2)}{(\mu_x^2+\mu_y^2+c_1)(\sigma_x^2+\sigma_y^2+c_2)}$$

, where higher value indicates better result.

Conclusion & Future work

- Using extension of cGAN can greatly improve the performance of a generative model.
- Due to the limitation of GPU memory, the batch size during training phase is only set to 1 and it might cause the model hard to converge.
- For future work, we plan to utilize model parallelism to increase batch size and develop a reinforcement-learning-based method to optimize wind turbine yaw control systems.

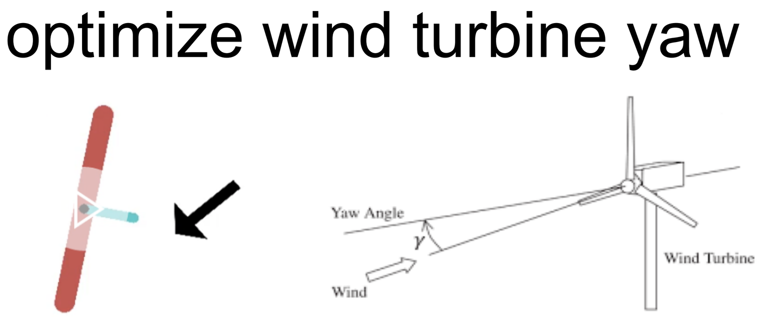


Figure 4: Yaw control systems are used to keep the wind turbine aligned with the wind direction.