EGU General Assembly - ERE2.2

Hybrid wind power forecasting model (WRFv4.1.3 and Artificial Neural Network) considering roughness sublayer characteristics

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YONSEI UNIVERSITY
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This presentation participates in OSPP
Outstanding Student & PhD candidate Presentation contest

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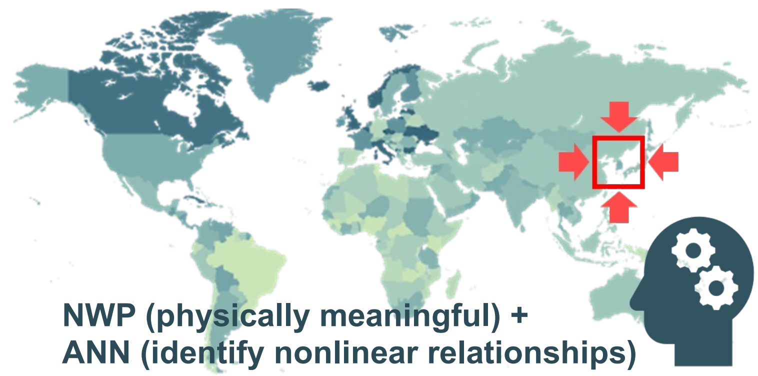
Introduction

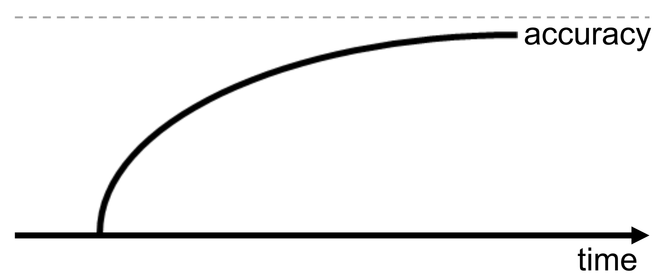
Motivation

- Higher wind power forecasting accuracy is needed for a stable replacement to renewable energy.

- Hybrid methods (Physical & Statistical) have mainly suggested and developed.
  Numerical Weather Prediction   Artificial Neural Network

- The accuracy seems to have reached a certain saturation level (about 15% NMAE).



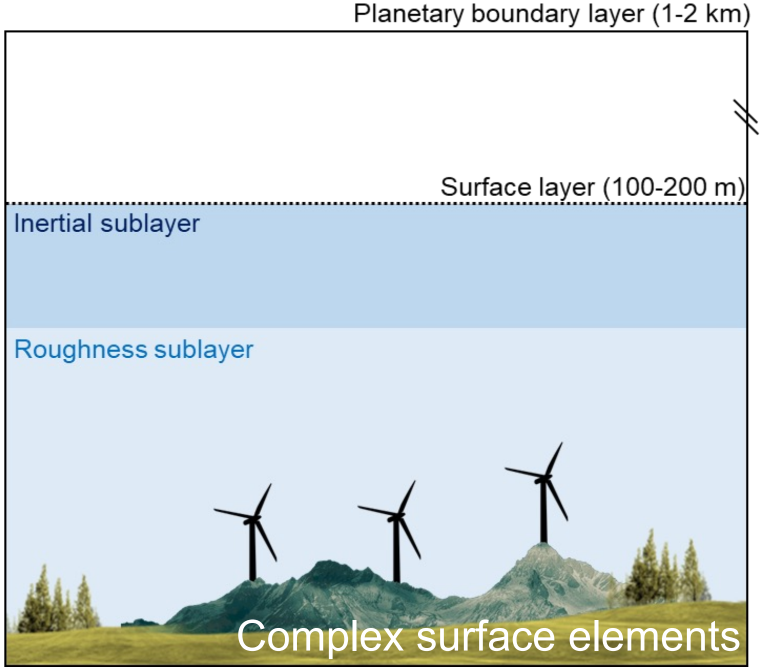


"Necessary to improve the fundamental performance of numerical weather prediction (NWP) models"

Introduction

- Wind turbines located in roughness sublayer (RSL)
- The surface layer is parameterization based on Monin-Obukhov similarity theory (MOST)
- RSL deviates from the MOST & NWP model simulates incorrect wind at RSL

➔ This study confirm improved wind power forecasting accuracy by reflecting the characteristics of RSL and complex surface in WRF model.



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RSL model

- Suggested by Harman and Finnigan (2007, 08)
- Implemented in WRF by Lee et al. (2020)

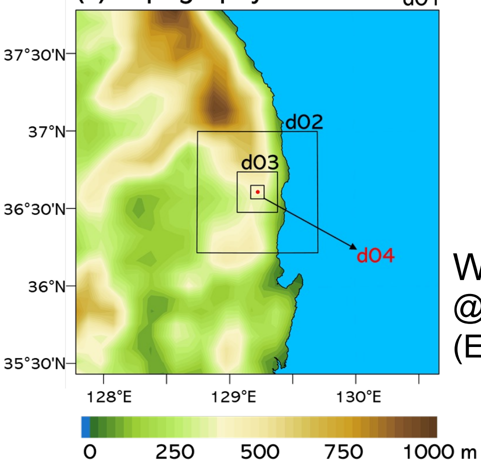
Complex surface

- Sub-grid orography option (Jiménez and Dudhia, 2012; Lee et al., 2015)
- Canopy height observed by spaceborne Lidar (Lee and Hong, 2016)
- Mountain slope effect (Garnier et al., 1968)
- Mountain shade effect

Methodology

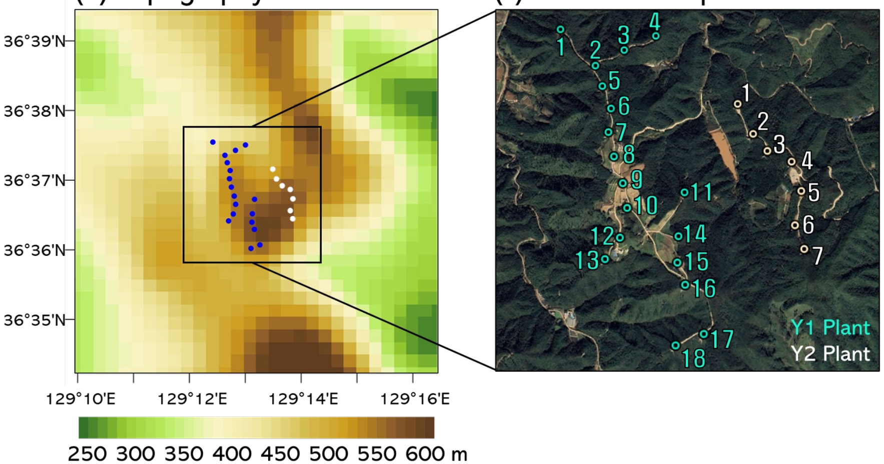
Step1. Wind speed forecasting with WRF model

(a) Topography



Wind farm
@Yeongyang-gun
(East part of South Korea)

(b) Topography of domain 4 (c) Wind turbine position



Model	Weather Research and Forecasting ver. 4.1.3			
Domain	**d01**	**d02**	**d03**	**d04**
Horizontal resolution (km)	9	3	1	**0.333**
Grids	31 x 31 grids for all domains			
Vertical resolution	33 Levels (up to 50 hPa)			
Geographic data	USGS 30s			
IC & BC	**NCEP Global Forecast System (GFS) 0.25°**			
Period	**2020.01.01 – 2020.12.31 (develop model)** **2021.01.01 – 2021.02.28 (validate model)**			

Physics package	
Microphysics scheme	WSM6 microphysics scheme
Radiation scheme	RRTMG for shortwave radiation scheme RRTMG for longwave radiation scheme
PBL scheme	Yonsei University PBL scheme
SFC layer scheme	**Revised MM5 surface layer scheme (CTL)** **Yonsei University surface layer scheme* (RSL)**
Cumulus scheme	Kain-Fritsch scheme
Land surface model	Noah LSM

*Lee et al. (2020)

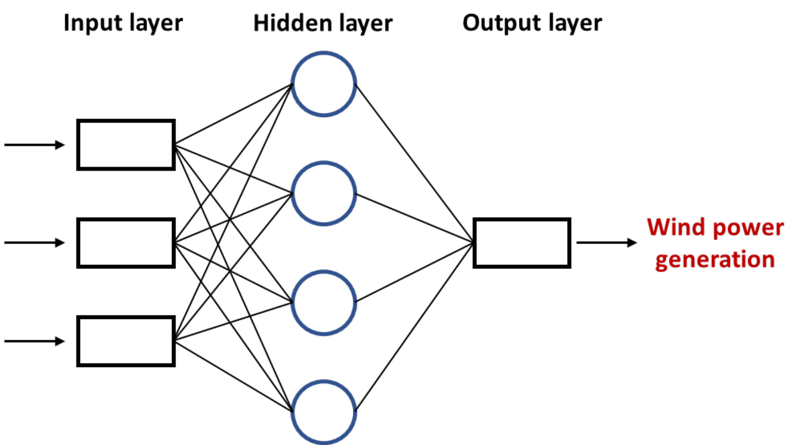
+ Sub-grid orography / Canopy height / Mountain slope / Mountain shade effects are considered

Methodology

Step2. Wind power forecasting with ANN

ANN model set up

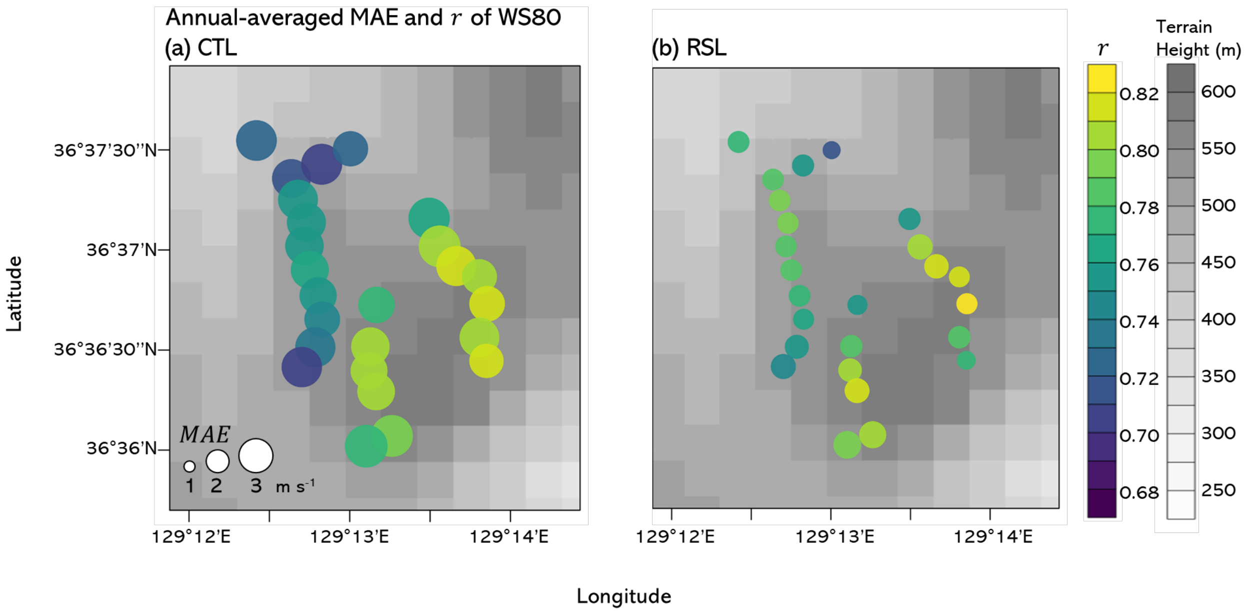
- Training function: Levenberg-Marquardt backpropagation algorithm
- Transfer function: Hyperbolic tangent sigmoid & Symmetric saturating linear function
- Data set divided into 70, 15, and 15% of training, test, and validation
- Three layers: input-hidden-output layers

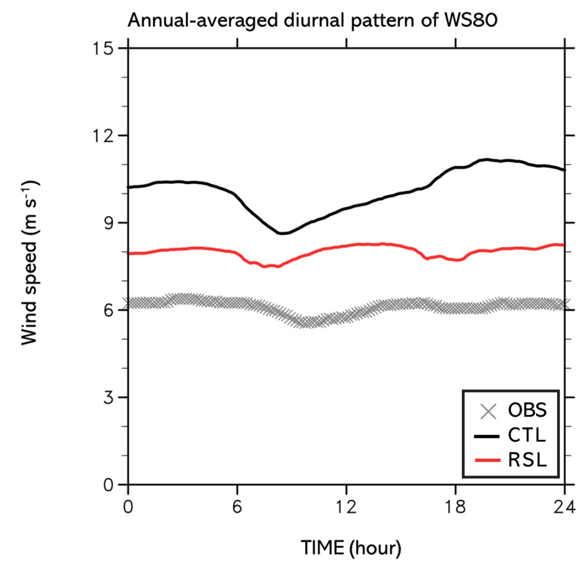


EXP	Description
ANN-M	ANN model using only the modeled wind speed by CTL and RSL
-MT	Add time variables (fuzzy set) to ANN-M experiment
-MO	Add 2-day prior observed diurnal wind speed to ANN-M experiment
-MTO	Add all the time variables and observation to ANN-M experiment

Results

Wind speed simulation with WRF model





Improved wind speed simulation in RSL experiment

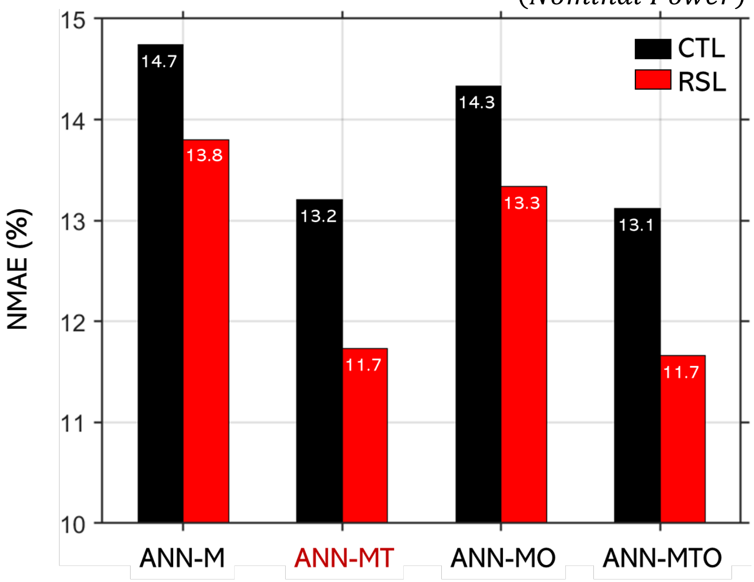
- Mean absolute error (*MAE*) decreases (4.3 ➔ 2.5 m s^{-1})
  Correlation coefficient (*r*) slightly increases (0.76 ➔ 0.78)

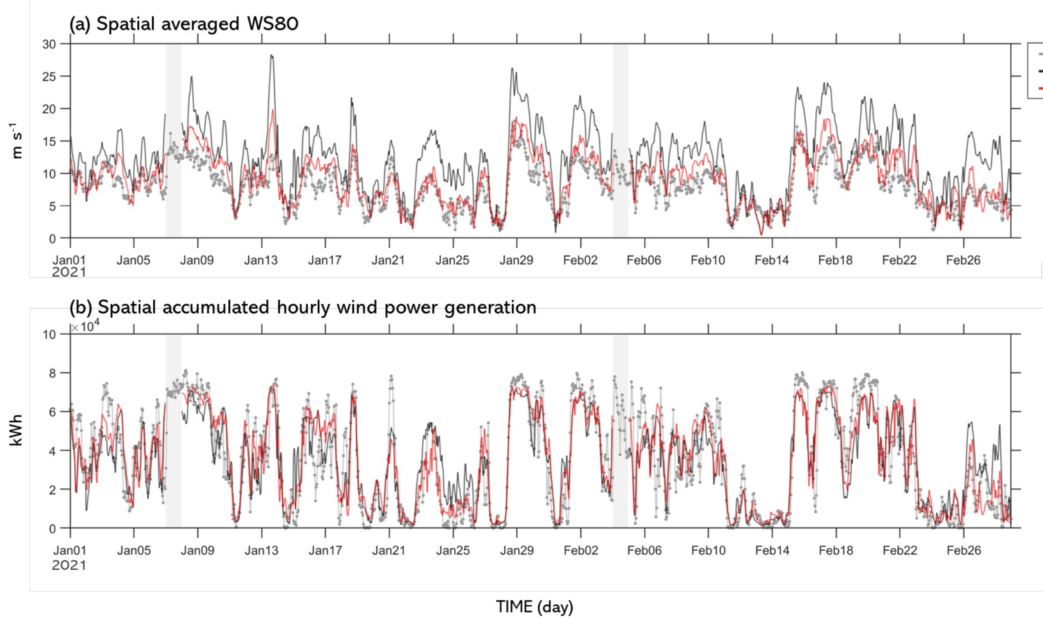
- Daily fluctuation range also becomes similar to observations.

Results

Wind power forecasting model with ANN

$$NMAE = \frac{\frac{1}{n}\sum_{i=1}^{n}|x_i - obs_i|}{(Nominal\ Power)}$$

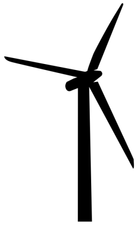




- The *NMAE* of wind power predicted by ANN decreases with improved wind speed input (14.7 ➔ 13.8%)
- When daily and seasonal changes are considered, ANN shows a significant improvement.
- The wind speed observed two days ago does not make a significant contribution.

Summary

- We improved the accuracy of wind power prediction through accurate wind speed simulation.
- Proper consideration of roughness sublayer and surface characteristics in WRF can make a significant improvement in wind speed simulation.
- When developing a wind power forecasting model, it is necessary to think more fundamentally about the prediction performance of NWP model.



Thank you

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