Response Letter

We sincerely thank the program committee and all reviewers for their valuable feedback that we have used to improve the quality of our paper. The reviewer comments are laid out below in *italicized font* and specific concerns have been numbered. Our response is given in normal font and changes/additions to the paper are given in blue text.

- Reviewer 1:
  Comments:
  1. *Figure 6 shows actual and predicted wind power on farm 2. The unit of y axis is not given. I assume it is MW. Since the base line of wind power is less than 1MW, I do not think the proposed method shows its advantage for predicting the wind power accurately.*
     Response:
     - The data was normalized by the respective nominal capacities of the wind farms. The normalized power values are between 0 and 1 (i.e., the percentage output), so the maximum power is not 1MW. We fixed the unit on y-axis and added a sentence about normalized data in section 2B:

       The data is collected from Global Energy Forecasting Competition 2012 - Wind Forecasting [12]. It consists of NWP wind speed & direction forecasts and actual wind power measurement. All power values have hourly resolution and were normalized between 0 and 1. This enables a scale-free comparison of the forecasting results on various wind farms. The NWP forecast outputs are available twice daily at 00UTC and 12UTC and has forecast horizon of 48 hours ahead. Thus, for each datetime, there are 4 NWP forecasts with different forecast horizons. Figure 1 shows the NWP forecast pattern.

     - The main objective of this research is to improve the existing best methodology and propose a generic wind power forecasting model. The original characteristics of the wind farms were masked and not used in our approach. The normalized data enables scale-free comparison of the forecasting results for various wind farms.

  2. The unit of RMSE and MAE are also not given in Tables IV and V.
     Response:
     - The power values were normalized to 0-1 range. We modified the text in section 4 to clarify it.

       The dataset comes from a Kaggle competition1, in which hundreds of teams have submitted their prediction results. The performance of the proposed approach is compared with the winner's approach [15] as well as two neural network models Node Decoupled Extended Kalman Filter trained Recurrent Neural Network (NDEKF RNN) [17] and AWNN [9]. The performance of the prediction models is evaluated by RMSE and MAE. Note that all power values were normalized to 0-1 range, which enables scale-free comparison on multiple farms.

       In this work, we proposed a three-layer hybrid model for wind power prediction. Experiment results on the same public dataset show that our model has the best performance compared with several existing approaches (Table IV). It also shows the prediction error for single models in each layer and for the hybrid model. RMSE of the proposed hybrid model is 0.14508, which outperforms the state-of-the-art approach and the neural network models. The performance of persistence model and random guess are also listed for reference.

- Reviewer 2:

  Comments: *The paper proposes a new hybrid model that predicts wind power generation based on meteorological forecast. The proposed hybrid model contains three layers which take account of wind speed, turbine inertia, seasonality, and wind farm location. The following comments/questions are raised for the authors' consideration:*

  1. *On the second page of the paper, the authors argue that "A major challenge of this problem comes from the instability of wind power generation. Another challenge part is the time-series nature of the data. Both problems are addressed by...". No explanation is given regarding how the "instability" and "time series" nature of the data present a challenge. Some elaboration is desirable to help audience appreciate the challenge being solved and the effectiveness of the prediction tool developed by the authors. The reviewer assumes that the authors mean to say "variability" of wind power generation. If this is the case, "instability" would be a mis-use and refer to something else in the domain of power system stability.*

     Response:

     - Thanks for your comments. We have changed "instability" to "variability". It's a mistake, as we already use "variability" in several paragraphs in both abstract and introduction.

     - We have added explanation of the "major challenges" in wind power forecasting in section 2A.

       A major challenge of this problems comes from the unpredictable nature and variability of wind conditions, especially the difference between meteorological wind forecasts and the actual wind condition at specific wind farm locations and altitudes due to microclimate. Another issue is the time-series nature of the data that inherits the long-term dependencies and seasonal effects of wind. Traditional time-series models like Autoregressive Integrated Moving Average (ARIMA) cannot formulate such non-linear relationships and incorporate all these effects. We address those issues by training a hybrid model and extract features from the following three aspects:

  2. *In Fig. 2, notations "f0, f1, f6..." are used multiple times across the paper but lacks description. Please provide a definition of the notations.*

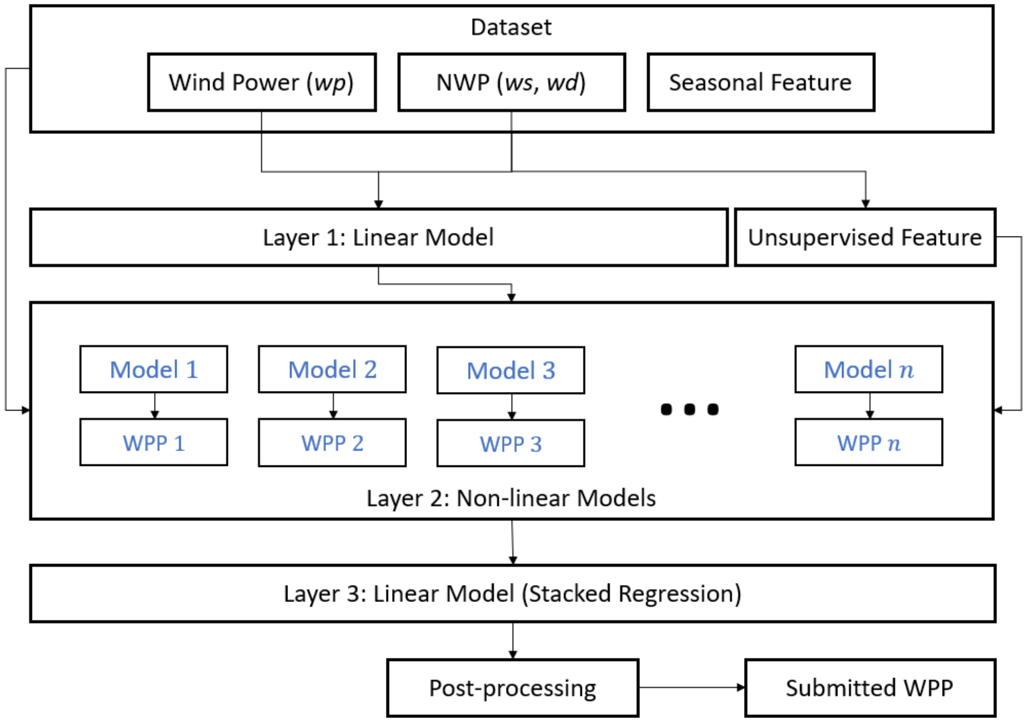
     Response:

     - The description of "*f0, f1, f6...*" was already given in Table III. They are prediction models used in Layer 2. The symbol "*f*" represents a prediction function ($y = f(x)$) that takes input feature x and output predicted power value y.

     - We have changed the title of Table III to "The layer 2 models and associated features", and changed "f0, f1, …" to italicized font "*f0, f1, …*" to avoid misleading.

f0	Prediction Model 0
f1	Prediction Model 1
f6	Prediction Model 6
f7	Prediction Model 7
f10	Prediction Model 10
f11	Prediction Model 11
f12	Prediction Model 12
f13	Prediction Model 13
f15	Prediction Model 15

     - We also revised Fig.2 to clarify this comment. Since Fig.2 is introduced early without model description, we have made it more generic.


Dataset
Wind Power (wp)
NWP (ws, wd)
Seasonal Feature
Layer 1: Linear Model
Unsupervised Feature
Model 1
Model 2
Model 3
Model n
WPP 1
WPP 2
WPP 3
WPP n
Layer 2: Non-linear Models
Layer 3: Linear Model (Stacked Regression)
Post-processing
Submitted WPP