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Optimal Ensemble Forecasting Method for One-Day Ahead Hourly Wind Power Forecasting

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***Abstract*—This paper proposes an optimal ensemble method for short-term wind power forecasting. Ensemble forecasting method that incorporates several single models to improve prediction error has been widely applied in renewable energy forecasting. In this paper, a k-means method is used to assort wind power and wind speed data into five different types. Five different machine learning models are created and then used to produce initial prediction. The swarm intelligence methods, including particle swarm optimization (PSO), salp swarm algorithm (SSA) and whale optimization algorithm (WOA), are used to optimize the weight allocation for each single model. The final prediction is then generated using the weighted sum of each single prediction model. A wind power generation system that is located in Changhua, Taiwan is used to validate the proposed method. Testing results show that the proposed method provides more stable and accurate prediction than each single model. The proposed method also allows more accurate predictions compared to Least Absolute Shrinkage and Selection Operator (LASSO) and ridge regression methods.**

***Index Terms*-- ensemble forecasting method, swarm intelligence, wind power forecasting, whale optimization algorithm**

I. Introduction

According to the important energy policy of the non-nuclear homeland, Taiwan's renewable energy plans to reach 20% by 2025. The wind power capacity will reach 4.2 GW. The power output of the wind turbine is intermittent and will have a great effect on the power grid. The security of the power grid may be compromised and the operating cost may increase. The effect of wind power forecasting includes power source management, reservation of backup capacity and operating costs. However, the wind is irregular and changeable that leads to uncertainty in wind power prediction, which affects power source dispatching. It is critical to provide an accurate prediction for efficient power source management.

Many researches on wind power prediction are presented in the literature. These studies can probably be classified into indirect method and direct method. Indirect method forecasts wind speed using historical wind speed and meteorological information [1]-[2]. A machine learning or a power curve is used to address the non-linear relationship between wind speed and wind power [3]. Direct method uses historical wind power and meteorological information to create a machine learning-based wind power prediction model [4]-[5].

Ensemble method was early used for weather forecasting. Recently, it is widely used to improve wind power forecasting accuracy. Ensemble method incorporates several prediction models to remain model diversity and avoid overestimation or underestimation. In [6], the authors divide ensemble method into competition and cooperation methods. The former generates datasets using different parameters to create diverse models. The final prediction is produced by the average of the output of each model. The latter establishes a prediction model to incorporate the output of several single models, which can be the statistical model, machine learning model or hybrid model.

For the competition method, reference [7] used meteorological data to establish individual models. A LASSO regression is then used to combine the output of each meteorological model. Testing results indicate that the LASSO regression gives more accurate than the benchmark methods. In [8], a ridge regression method is used to incorporate five random forest methods for photovoltaic power prediction. A Bayesian optimization algorithm is used to tune the hyperparameters for the ridge regression model. Another research uses ridge regression method to incorporate several machine learning methods for renewable energy prediction [9]. A method that uses the average of the outputs of each single model is presented for wind speed prediction [10]. In [11], a recurrent neuron network (RNN) is used to incorporate several models for photovoltaic power prediction.

This paper proposes a cooperative ensemble method to incorporate five prediction models for one-day ahead hourly wind power forecasting. First, the k-means method is used to classify historical wind speed and wind power data into five different categories. An initial forecast is generated using each single machine learning model such as the random forest (RF), support vector regression (SVR), long short-term memory (LSTM), recurrent neural network (RNN) and K-nearest neighbors (KNN) models. To optimize the weight allocation for each single prediction model, the swarm intelligence methods, including PSO, SSA and WOA, are used to produce the final prediction. Furthermore, a RF model is used to modify the wind speed prediction from a prediction platform. The contributions of this paper are summarized as follows:

(1) To decrease the prediction error, 25 prediction models are created using five individual models with five categories of data.

(2) To avoid overfitting, the proposed method optimizes the weight allocation for five single prediction models

and allows more accurate prediction than single prediction models.

(3) A large prediction error for wind speed is generated from a prediction platform. This paper uses a random forest model to modify the wind speed prediction that improves wind power prediction error by 2-3%.

The rest of this paper is as follows. Section 2 introduces the traditional ensemble methods. Section 3 describes the proposed ensemble method. Testing results are described in Section 4. Section 5 provides the conclusions.

II. Ensemble Methods

2.1 The average method

By averaging the outputs of each prediction model, the average method can be expressed as [6, 10]:

$$\tilde{Y}_{out} = \frac{1}{N}\sum_{k=1}^{N}\tilde{y}_k \quad (1)$$

where $\tilde{Y}_{out}$ is the final prediction, N is the number of each single model and $\tilde{y}_k$ is the output of the kth single model.

2.2 The weighted sum method

Giving different weights, the weighted sum method incorporates the outputs of the single model to provide the final prediction as follows [6]:

$$\tilde{Y}_{out} = \frac{1}{N}\sum_{k=1}^{N} w_k \times \tilde{y}_k \quad (2)$$

where $w_k(\geq 0)$ is the weight of the kth single model and the sum of the weights is 1.

2.3 LASSO method

LASSO is an ensemble method that use a Bayesian optimization algorithm to determine the weight of each single model [7-8]. LASSO regression can avoid overfitting and has the ability to give adequate weight for each predictor as follows:

$$\tilde{Y}_{out} = \sum_{k=1}^{N} w_k \times \tilde{y}_k \quad (3)$$

where w_k can be expressed as:

$$\min_{w\in R^N}\left\|\tilde{Y}_{out}w - Y_{out}\right\|_2 + \delta\|w\|_2 \quad (4)$$

where Y_{out} is a real prediction output. The term $\|w\|_2$ is the square root of a norm and δ (≥0) is a parameter that dominates the magnitude of the weights.

2.4 Ridge regression method

Unlike the LASSO method, ridge regression uses the square of the weights to determine the weight of each model as follows [8-9]:

$$\min_{w\in R^N}\left\|\tilde{Y}_{out}w - \tilde{Y}_{out}\right\|_2 + \delta w^2 \quad (5)$$

2.5 Stacking method

The stacking method uses machine learning algorithm to determine the weights of each single model. The learning result varies according to the method used. In [11], a RNN is used to incorporate several models for solar power prediction. Differing from the stacking method, this paper uses a swarm intelligence algorithm to determine the weights for each single prediction model.

III. The Proposed Ensemble Method

In this paper, a swarm intelligence algorithm is used to reasonably allocate the weight for each single model. Details of the structure are shown in Fig. 1. First, model 1 (RF) to model 5 (KNN) are used to generate a preliminary prediction. Once the weights of each model have been properly assigned using a swarm intelligence algorithm, the final predictions are generated by aggregating the outputs of each model. In the following subsection, the WOA optimization algorithm is introduced. Details of PSO and SSA methods can refer to [12] and [13], respectively.

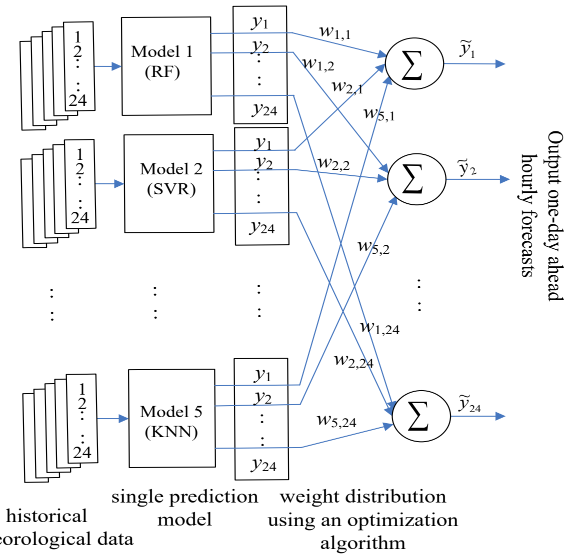

Fig. 1. Structure of the proposed method.

3.1 WOA

WOA emulates the fishing behavior of the humpback whale and was presented by Mirjalili and Lewis in 2016 [14]. The fishing strategies used by humpback whale are described as follows:

(1) The prey encircling strategy

When humpback whales find fish location, the prey encircling strategy is used as:

$$\vec{Q}(t+1) = \vec{Q}_*(t) - \vec{R}\cdot\vec{S} \quad (6)$$

$$\vec{S} = \left|\vec{H}\cdot\vec{Q}_*(t) - \vec{Q}(t)\right| \quad (7)$$

where $\vec{Q}(t+1)$ is the next position, $\vec{Q}_*(t)$ is the prior best position, "·" is an inner product, $\vec{R}\left(= 2\vec{r}\cdot\vec{h} - \vec{r}\right)$, $\vec{S}$ and $\vec{H}\left(= 2\cdot\vec{h}\right)$ are constants, $\vec{h} \in [0, 1]$ is a random number with uniform distribution, $\vec{r}$ is decreased from 2 to 0 and $\vec{R}$ is set between 0 and 1.

(2) The bubble attacking strategy

Humpback whales uses bubbles to scare schools of fish. The next step is to surround and attack fish. The bubble attacking strategy used by humpback whales is expressed as follows:

$$\vec{Q}(t+1) = \begin{cases} \vec{Q}_*(t) - \vec{R}\cdot\vec{S}, & if\ u < 0.5 \\ \left|\vec{Q}_*(t) - \vec{Q}(t)\right| \cdot e^{a\theta} \cdot \cos(2\pi\theta) + \vec{Q}_*(t), & if\ u \geq 0.5 \end{cases} \quad (8)$$

Where the term $\left|\vec{Q}_*(t) - \vec{Q}(t)\right|$ defines the distance between the whales and the fish, a dominates the shape of the spiral curve, $\theta \in [0,1]$ and $u \in [0,1]$ are random numbers. The bubble attacking strategy by humpback whales is shown in Fig. 2.

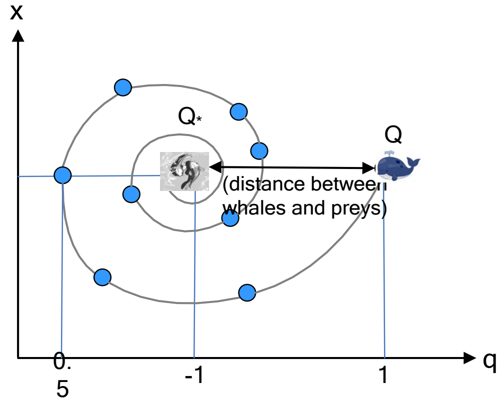

Fig. 2. The bubble attacking strategy by humpback whales [14].

(3) The search for exploration strategy

The humpback whales also search for other fishes using $|R| > 1$ to enhance exploration and decrease the probability to stuck in a local optimum. The search for exploration strategy is expressed as:

$$\vec{Q}(t+1) = \vec{Q}_r - \vec{R}\cdot\vec{S} \quad (9)$$

$$\vec{S} = \left|\vec{H}\cdot\vec{Q}_r - \vec{Q}(t)\right| \quad (10)$$

where $\vec{Q}_r$ is randomly generated from the whale swarm.

3.2 The steps for allocating the weights

Details of the steps to allocate the weights for each single prediction model using a swarm intelligence algorithm are summarized as follows:

Step 1: Randomly generate initial feasible solution as follows:

$$z_{i,j}(0) = z_{i,min} + u_j \times \left(z_{i,max} - z_{i,min}\right),$$
$$i = 1,2,\dots,V, j = 1,2,\dots,F \quad (11)$$

where $z_{i,j}(0)$ is the ith variable of the jth initial feasible solution, $z_{i,max}$ is the maximum value, $z_{i,min}$ is the minimum value, $u_j \in [0, 1]$ is a uniform random number, V and F are the respective number of variables and feasible solutions. The jth feasible solution can be expressed as follows:

$$z_j = [w_1^t, w_2^t, \dots, w_5^t],\ t = 1,2,\dots,24,$$
$$j = 1,2,\dots,F \quad (12)$$

$$\sum_{i=1}^{5} w_i^t = 1, w_i^t \geq 0 \quad (13)$$

where w_i^t is the weight of the ith single model. Note that w_i^t is larger than or equal to zero and the sum of the weights is 1.

Step 2: Calculate he fitness value for each initial feasible solution. The particle with the best fitness value is stored. The fitness value of the jth feasible solution is expressed as follows:

$$f_j^t = \sum_{i=1}^{5}(\tilde{y}_i^t \times w_i^t - y_i^t)^2 \quad (14)$$

where $\tilde{y}_i^t = [\tilde{y}_1, \tilde{y}_2, \dots, \tilde{y}_T]$ is the forecasted value of the ith model, $y_i^t = [y_1, y_2, \dots, y_T]$ is the real value of the ith model and T is the number of training data.

Step 3: Update position for each feasible solution as follows:

(1) SSA: respectively modify the positions of the leader salp and the follow salps.

(2) PSO: update position and velocity for each particle.

(3) WOA: use fishing strategies to modify the position of the humpback whales as shown from (6) to (10).

Step 4: Use (14) to calculate the fitness value for each modified feasible solution. The solution with the best fitness value in the swarm is chosen as the survivor and passed to the next generation.

Step 5: Check whether the 24-hour weighting allocation is finished if the maximum iteration is reached. Output weight allocation for the 24 hours if it satisfies the stop condition. Otherwise, repeat step 3 to step 5.

IV. Simulation Results

4.1 Data processing

A 3.6 MW wind power generator located in Changhua, Taiwan is employed to validate the proposed method. The historical data including wind power, wind speed and wind direction are collected from January 2020 to December 2020. The data resolution is 1 hour each point. After removing outliers or unusual data, 70% of the data is used for training, 15% for validation, and the rest for testing. The wind speed and wind direction are measured at a height of 10 meters from the hub. Because the wind blades are installed at a height of 67 meters, the measured data must be converted to the same altitude in order to meet the actual situation. The conversion formula is expressed as follows [15]:

$$\frac{v_{d_2}}{v_{d_1}} = \left(\frac{d_2}{d_1}\right)^{\varphi} \quad (15)$$

where v_{d_2} and v_{d_1} represent the wind speed at 67 (m) and 10 (m), respectively. d_2 is 67 (m) and d_1 is 10 (m). φ is a constant, which represents the surface friction coefficient and is set by experiment. For the sky with rough blocking area, the φ is high and is low in the smooth area. φ is usually set between 0.1 and 0.4. In this paper, φ is set at 0.2. This paper uses Python software to design the codes for each single model and optimization algorithm.

Figure 3 indicates the wind power scatter curve before data processing. In this case, the Pearson correlation coefficient between wind speed and wind power is low. After removing outliers or abnormal data, the correlation coefficient between wind speed and wind power reaches 0.96, and is -0.51 for wind power and wind direction. As shown in Fig. 4, the wind power data is divided into five classes according to the order of wind power using a k-means method. The criterion of mean relative error (MRE) is employed to evaluate the prediction accuracy as follows:

$$MRE = \frac{1}{T}\sum_{k=1}^{T}\frac{|y_k-\tilde{y}_k|}{y_{peak}} \times 100\% \qquad (16)$$

where T is the number of validation or testing data, y_k is the kth measured value, $\tilde{y}_k$ is the kth forecasted value, y_{peak} is the capacity of the wind turbine which reveals the ability to output maximum power.

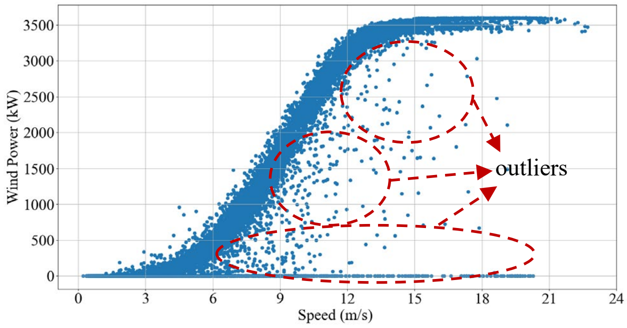

Fig. 3. Wind power scatter curve before data processing.

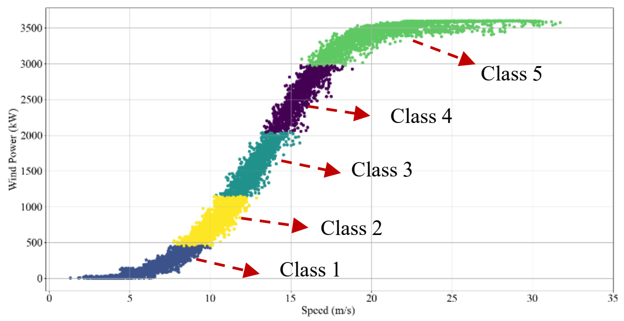

Fig. 4. Data category for wind power.

4.2 Simulation results

To generate initial prediction, this paper uses RF, SVR, LSTM, RNN and KNN as a single model, where the inputs are hourly wind speed and wind direction and the output is hourly wind power. After getting the initial forecasts, a swarm intelligence algorithm is used to optimize the weight allocation for each single model. To clearly observe the 24-hour iteration curves, the curves from the 51st to 80th iterations using a WOA method are enlarged and shown in Fig. 5. Most curves converge within 50 iterations. The average iteration time for the 24 hours is about 134 (s). The average execution time for SSA and PSO needs about 113 (s) and 101 (s), respectively. PSO takes less time to achieve optimization due to its simpler operation.

Table I displays the weight allocation for each single model obtained by the WOA algorithm. A larger weight represents a greater impact on the output. A weight equal to 0 means it is no impact on the output. The SSA and PSO are also used to produce the weight allocation for each single prediction model. Due to space limit, they are not displayed in this paper.

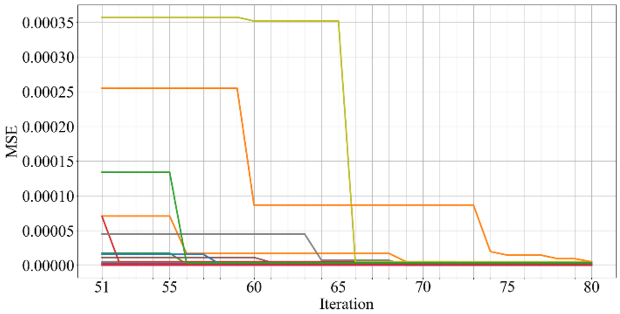

Fig. 5. 24-hour curves from 51st to 80th iterations using a WOA method.

TABLE I

THE WEIGHTS FOR EACH SINGLE MODEL USING A WOA ALGORITHM.

Time	RF	SVR	LSTM	RNN	KNN
1st hour	0.804	0.000	0.000	0.022	0.151
2nd hour	0.050	0.002	0.005	0.991	0.000
3rd hour	0.002	0.001	0.005	0.015	0.995
4th hour	0.026	0.011	0.705	0.001	0.243
5th hour	0.076	0.441	0.168	0.244	0.000
6th hour	0.492	0.002	0.423	0.000	0.037
7th hour	0.633	0.001	0.162	0.231	0.001
8th hour	0.048	0.501	0.011	0.355	0.019
9th hour	0.651	0.002	0.005	0.211	0.125
10th hour	0.962	0.006	0.000	0.000	0.006
11th hour	0.974	0.010	0.006	0.001	0.001
12th hour	0.149	0.000	0.000	0.843	0.004
13th hour	0.003	0.230	0.736	0.002	0.000
14th hour	0.002	0.374	0.002	0.608	0.000
15th hour	0.028	0.645	0.109	0.007	0.166
16th hour	0.000	0.003	0.001	0.996	0.010
17th hour	0.002	0.000	0.182	0.625	0.192
18th hour	0.528	0.012	0.053	0.344	0.054
19th hour	0.285	0.076	0.001	0.658	0.006
20th hour	0.125	0.120	0.019	0.000	0.730
21st hour	0.000	0.002	0.011	0.006	0.991
22nd hour	0.003	0.045	0.217	0.515	0.189
23rd hour	0.007	0.008	0.000	0.050	0.951
24th hour	0.003	0.000	0.001	0.004	1.000

This paper uses an indirect method to make the one-day ahead hourly wind power forecasting. The wind speed and wind direction prediction data are attained from a Solcast forecasting platform [16]. However, the forecasting platform produced a high forecast error of approximately 16.3%. To improve the forecasting accuracy for the wind speed, a RF model is established to address the non-linear relationship between actual and forecasted wind speed. In the training stage, the inputs are the wind speed and wind direction predictions obtained from Solcast and the output is the actual wind speed. In the testing stage, the wind speed predictions are obtained from the RF model, and the resulting prediction error decreases from 16.3% to 4.6%. The wind speed forecasting data obtained from a RF model are then used to predict wind power for each single model.

Figure 6 indicates the forecasting curves for different methods on March 24, 2020. The forecasting error for SSA, PSO and WOA are 5.9384%, 5.8768% and 5.8841%, respectively. Figures 7 and 8 separately show the forecasting results on June 6 and November 25, 2020. The errors produced by the three methods are very close.

Table II shows the comparison between the single models and the ensemble models. Forecasting results for 24 testing days are presented in this table. Among all single models, RNN achieves lower average prediction error. Comparing to the ensemble models, the single models allow less forecast accuracy. Furthermore, RF has 10 testing days that produced the worst forecast (noted with w), but 3 testing days that produced the best forecast (noted with b). None of the ensemble models give the worst prediction from the 24 testing days. Results of this table indicate that the ensemble models give more stable and accurate forecasting results than the single prediction models.

Table III reveals the comparison for three different cases: case 1 is tested with actual wind speed, case 2 is tested with Solcast's wind speed prediction and case 3 is tested with wind speed correction using RF model. In case 1, WOA predicts the best while RNN gives the worst prediction. In case 2, SVR gives the best forecast and three ensemble models provide predictions close to the average error of the five individual models. In case 3, SSA gives the best prediction while KNN predicts the worst. This case also shows that the ensemble model predicts better than the single predictive models. Compared with case 2, case 3 reduces the prediction error by 2~3%. Table IV shows the comparison between different ensemble methods. The LASSO [7] and ridge regression [9] use a Bayesian optimization algorithm to optimize the weight allocation for each single model. Testing with 24 datasets shows that LASSO is unstable that has 9 testing days to produce the worst forecast (noted with w) and 8 testing days to produce the best forecast (noted with b). Based on the average prediction error, the proposed ensemble method allows more accurate prediction than LASSO and ridge regression methods.

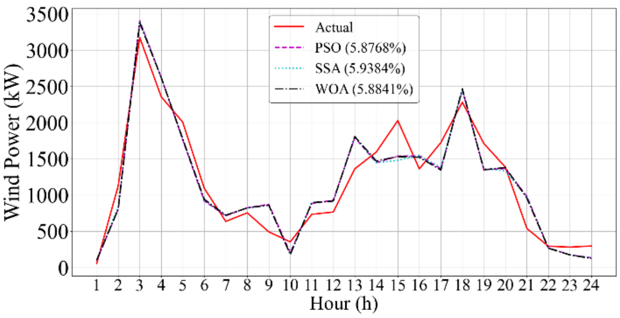

Fig. 6. Forecasting curves for different methods on March 24, 2020.

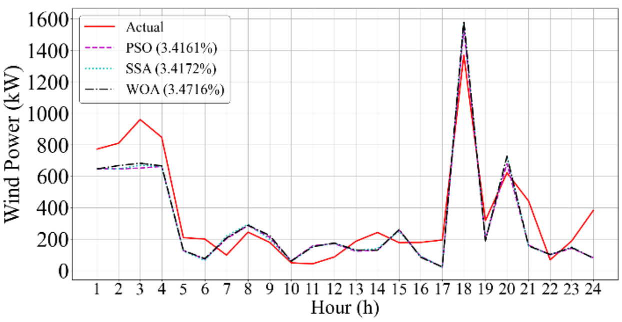

Fig. 7. Forecasting curves for different methods on June 6, 2020.

V. Conclusions

A one-day ahead hourly wind power forecasting is proposed using an ensemble method. A total of one-year historical data including hourly wind power, wind speed and wind direction are collected. After removing outliers or unusual data, a k-means method is used to classify the data into five different classes based on the wind power and the associated wind speed. Five machine learning models are employed to construct the individual model using each class of data. The initial predictions are generated by each single machine learning model. To acquire the optimal weight allocation for each single model, a swarm intelligence algorithm such as SSA, PSO and WOA is used and provides the final prediction accordingly. Testing on a wind power generation system indicates that the proposed ensemble models allow more stable and accurate forecast than the single prediction models. Three different cases are used to verify the proposed method. Comparing to case 2, case 3 decreases prediction error by 2~3%. The proposed method is also compared with other ensemble methods such as LASSO and ridge regression and gives more accurate predictions.

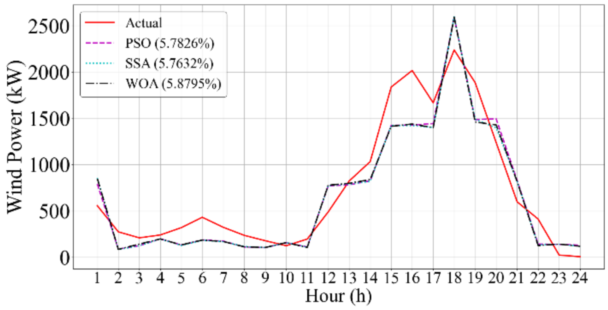

Fig. 8. Forecasting curves for different methods on November 25, 2020.

TABLE II
COMPARISON BETWEEN SINGLE AND ENSEMBLE MODELS.

Date (2020)	Five single models					Three ensemble models		
	RF	SVR	LSTM	RNN	KNN	SSA	PSO	WOA
01/13	6.140	6.254[w]	6.143	6.168	5.747[b]	6.164	6.190	6.091
01/21	6.248	6.445[w]	6.161[b]	6.177	6.618	6.232	6.177	6.219
02/21	4.821	4.753	4.824[w]	4.768	4.551[b]	4.700	4.748	4.704
02/27	6.525	6.157	6.524	6.530	6.713[w]	6.150	6.282	6.393
03/15	7.927[w]	7.633	7.499	7.592	7.771	7.511	7.469[b]	7.517
03/24	5.773[b]	5.975	5.839	5.994	6.334[w]	5.938	5.876	5.884
04/08	6.075[b]	6.218	6.351	6.406[w]	6.681	6.313	6.310	6.336
04/27	5.694[w]	5.523	5.561	5.444	5.567	5.297	5.436	5.227[b]
05/12	5.930	5.968	6.003	5.998	6.335[w]	5.945	5.889[b]	5.926
05/23	7.005[w]	6.812	6.745	6.587	6.773	6.602[b]	6.757	6.695
06/06	6.612[w]	6.342	6.251	6.189	6.050[b]	6.314	6.361	6.303
06/09	3.405	3.329	3.426	3.315[b]	3.492[w]	3.417	3.416	3.471
07/09	6.382	6.400[w]	6.019	6.002[b]	5.250	6.205	6.287	6.219
07/16	6.677[w]	6.256	5.714[b]	5.794	4.964	6.215	6.176	6.170
08/13	2.873	2.772[b]	2.906[w]	2.865	2.832	2.801	2.825	2.853
08/26	5.681[w]	5.202[b]	5.445	5.404	5.658	5.299	5.338	5.573
09/21	5.770	5.510	5.932	5.900[w]	5.369[b]	5.882	5.724	5.818
09/25	6.662[b]	7.268	7.129	7.201	7.541[w]	7.080	7.029	7.077
10/09	6.612[w]	5.720	5.722	5.550[b]	6.506	5.745	5.575	5.605
10/26	5.685	5.728	5.723	5.661	6.035[w]	5.658	5.707	5.523[b]
11/14	5.452	5.602	5.626	5.564	5.757[w]	5.584	5.405[b]	5.511
11/25	5.926[w]	5.766	5.758	5.806	5.682[b]	5.763	5.782	5.879
12/23	5.883[w]	5.614	5.617	5.585	5.699	5.553[b]	5.630	5.616
12/29	5.657[w]	5.285	5.366	5.259	5.481	5.286	5.365	5.170[b]
Average	5.892	5.772	5.762	5.742	5.809	5.735	5.740	5.741

Note: [b]: The best forecasting result on that testing day.
[w]: The worst forecasting result on that testing day.

TABLE IV
COMPARISON OF THREE DIFFERENT CASES.

	Five single models					Three ensemble models		
Testing data	RF	SVR	LSTM	RNN	KNN	SSA	PSO	WOA
Case 1	2.295	2.276	2.334	2.338	2.251	2.277	2.281	2.230
Case 2	6.952	6.467	8.745	8.461	8.878	7.772	7.554	7.551
Case 3	5.892	5.772	5.762	5.742	5.809	5.735	5.740	5.741

Note: Case 1: wind speed using actual measured data.
Case 2: wind speed using Solcast forecasting data.
Case 3: wind speed prediction data using correction model.

TABLE III
COMPARISON BETWEEN DIFFERENT ENSEMBLE MODELS.

Date (2020)	LASSO	Ridge	SSA	PSO	WOA
01/13	6.133	6.139	6.164	6.190^{w}	6.091^{b}
01/21	6.409^{w}	6.199	6.232	6.177^{b}	6.219
02/21	4.736	4.733	4.700^{b}	4.748^{w}	4.704
02/27	6.368	6.371	6.150^{b}	6.282	6.393^{w}
03/15	7.422^{b}	7.568^{w}	7.511	7.469	7.517
03/24	5.734^{b}	5.900	5.938^{w}	5.876	5.884
04/08	6.040^{b}	6.316	6.313	6.310	6.336^{w}
04/27	5.483^{w}	5.364	5.297	5.436	5.227^{b}
05/12	6.018^{w}	5.960	5.945	5.889^{b}	5.926
05/23	6.826^{w}	6.676	6.602^{b}	6.757	6.695
06/06	6.316	6.338	6.314	6.361^{w}	6.303^{b}
06/09	3.465^{w}	3.406^{b}	3.417	3.416	3.471
07/09	6.186^{b}	6.271	6.205	6.287^{w}	6.219
07/16	6.294^{w}	6.179	6.215	6.176	6.170^{b}
08/13	2.861^{w}	2.828	2.801^{b}	2.825	2.853
08/26	5.571^{w}	5.408	5.299^{b}	5.338	5.573
09/21	5.654^{b}	5.809	5.882^{w}	5.724	5.818
09/25	7.054	7.071	7.080^{w}	7.029^{b}	7.077
10/09	5.935^{w}	5.739	5.745	5.575^{b}	5.605
10/26	5.502^{b}	5.606	5.658	5.707^{w}	5.523
11/14	5.342^{b}	5.514	5.584^{w}	5.405	5.511
11/25	5.812	5.802	5.763^{b}	5.782	5.879^{w}
12/23	5.521^{b}	5.625	5.553	5.630^{w}	5.616
12/29	5.330	5.340	5.286	5.365^{w}	5.170^{b}
Average	5.751	5.757	5.735	5.740	5.741

Note: ^{b}: The best forecasting result on that testing day.
^{w}: The worst forecasting result on that testing day.

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