Extended Hybrid Wind Power Forecasting Approach to Short-Term Decisions

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***Abstract*—The advantages of wind power integration over other renewable resources are well-known information and the natural results are the massive worldwide integration. Such massive integration, without the correct management together with conventional generation leads to an augmented complexity and the inflexibility of conventional power systems. For several reasons, forecasting tools are one of the most valuable tools in the power systems field, because they helps to decide in advance the way to manage correctly and with profits the electrical mix production. In this work, an extended hybrid wind power forecasting approach, with probabilistic features, is proposed to forecast twenty-four hours-ahead, considering only real historical wind power data. To validate the proposed forecasting approach, a comparison with other validated models is performed to offer a fair and proportional analysis. The outcomes show that the suggested forecasting approach performs adequately even considering the reduced data available as input.**

***Keywords—Adaptive neuro-fuzzy inference system, Hybrid forecasting approach, Monte Carlo simulation, Short-term decision, Wind power*.**

I. INTRODUCTION

Due to the utmost necessary new paradigm shift for an intelligent, decarbonized and sustainable power system, the challenges to its profitability and correct management are still considerable nowadays. One of the ways, the cheapest one, to cope with such challenges, it is with advanced tools and techniques that allow a real, robust and cost-effective approximation through the time series forecasting, helping to minimize the overall costs, increasing the power systems' flexibility, and improving the overall system operation [1].

Forecasting approaches still play an important key role for all market players, whether to estimate the renewable output potential, outlining the strategies to sell some amount of energy during a certain period, maximizing the profits or by the need to know how much renewable energy will have in a certain horizon time to determine the best combination production between the electricity mix [2]. However, renewable production, like wind power, introduces variability, volatility, randomness, i.e., uncertainty behavior, which increases the challenges in the accurate and timely management [3], turning the conventional power transmission inflexible, even more, when power systems feel the renewable massive integration or renewable's priority usage among the conventional generation.

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The previous and many other concerns, about renewable integration in power systems, are now increasingly higher when in a near-future end-customers are looked as active players in the electricity market, having distributed generation and storage features, and with the advent and expected integration of smart grid concepts [4].

Despite the efforts of the scientific community to present increasingly robust forecasting approaches with timely response, there is still a long way to minimize the errors' results, which are propagated throughout the decision or actions made [5]. Some examples of innovative forecasting models, available on the widespread information in the latest years are described in brief.

For instance, [6] was proposed a multi-scale forecasting approach, created on the combination of multi mapping network combined with stacked denoising auto-encoder. The forecasting period considered was settled for the next 24 to 72 hours ahead. The proposed model was divided in two stages and it was applied in a regional area, considering several wind farms.

In [7] a short-term forecasting approach was presented centered on outlier smooth transition autoregressive assembly, and joined with the comprehensive autoregressive conditional heteroskedasticity tool, and the fat-tail distribution technique. In this proposed model, one of the goals was the analysis of the outlier outcome of wind power considering the output influence and the regime-switching catalogue tool.

In [8] was presented a curve modeling and forecasting approach considering the errors and inconsistent data, which may be divided into heteroscedastic and error spreading with long-tail data. To this end, the heteroscedastic projection regression tool and the robust projection regression tool were proposed considering an optimized variational Bayesian criterion in the deterministic and probabilistic data, respectively.

In [9] a probabilistic multi-model combination approach was proposed, considering three different probabilistic tools centered on the Bayesian learning, kernel density approximation, and beta distribution approximation, solved by two-step optimization model to provide and analyze the different probability density functions for the probabilistic wind power output.

In [10] a short-term forecasting approach based on an innovative neural network and LightGBM was presented. The model was structured in three stages.

First, it was analyzed the data time-series features between different wind farms. Then, on the second stage, the innovative neural network was suggested to collect the features from input data, and the network parameters adjusted accordingly with the results. Finally, LightGBM classification tool was implemented to augment the overall forecasting results.

In [11] was presented a hybrid short-term forecasting approach considering a combination of variation mode decomposition, K-means grouping tool, and improved memory network, where the decomposition model was responsible to decompose the wind power data in different rates, the K-means was used to classify the similar data, and the improved memory network was the central tool of the hybrid tool, used to capture the unsteady features of each wind data component.

In [12] a hybrid forecasting system was presented to improve the forecasting output considering the deterministic and probabilistic features. The hybrid feature selection was based on the improved neural network strategy tool. Hence, an enhanced multi-objective optimization model was implemented to offer the optimal output for system constraints, and finally, the output was evaluated considering an evaluation module.

The central goals of this proposed work are shortened in three steps. First, a general overview about the recent advances on wind power forecasting approaches is addressed considering the limitation around the widespread information available in this field of knowledge. Second, the proposed manuscript presents a hybrid wind power forecasting approach, applied in the short-term time horizon, i.e., twenty-four hours-ahead, without exogenous data, i.e., considering only a partial part of real historical wind power data, and considering a successful combination between probabilistic tools and hybrid tools. The third step involves a comparison analysis considering the proposed hybrid wind power forecasting methodology, with some wind power benchmark model, in the short-term, considering the same historical wind power profiles, for a fair and comparative analysis between the involved forecasting models.

The remaining document is organized by the subsequent sections. Section II provides the proposed extended hybrid wind power forecasting approach. Section III provides the case study, the main and analysis results. Finally, Section IV provides the main findings and future guidance information.

II. WIND POWER FORECASTING APPROACH

A. *Forecasting Approach Overview*

The suggested extended hybrid wind power forecasting approach (EHWPF) is a successful tools combination, originally applied on the electricity market prices forecasting [13], which employs wavelet transforms in order to retain, save and smooth the random behavior of historical wind power data used as input.

Then, a hybrid particle swarm optimization, with differential and evolutionary features, offers augmented competences to the adaptive neuro-fuzzy inference system tool helping to decrease the calculation error by correcting the involvement functions, resulting in a preliminary result.

The preliminary result is then examined considering the Monte-Carlo simulation tool, analyzing the forecasted values' series without compromising the forecast error.

Further details about the mathematical principles of proposed EHWPF is available in [13, 14].

B. *Proposed Extended Hybrid Wind Power Forecasting*

The proposed EHWPF algorithm is described below and it is shown in Figure 1. The proposed EHWPF follows the following footsteps:

- Footstep 1: Start the EHWPF approach with a historic records of wind power, having as window period the forecasting time-window of three hours with a footstep of fifteen minutes (rows of twelve elements);
- Footstep 2: Choose the wind power records that will be treated by the wavelet transform tool;
- Footstep 3: Choose the constraints of the hybrid particle swarm optimization, with differential and evolutionary features (available in the Table I);
- Footstep 4: Choose the wind power record to the hybrid particle swarm optimization, with differential and evolutionary features, to attend the competences of the adaptive neuro-fuzzy inference system tool;
- Footstep 5: Choose the running details of the adaptive neuro-fuzzy inference system (available in the Table I);
- Footstep 6: Choose the wind power record as the input of the adaptive neuro-fuzzy inference system structure, in each iteration;
- Footstep 7: Compute the error results with the different analysis tools of error criterions:
  - o If the error objective is not reached, jump to Footstep 6;
  - o Else if the error is not achieved previously, jump to Footstep 4 to discover other set of rows as input data;
  - o Else if the greatest result output is not achieved, or the sum of the vaunting sets ends, save the greatest record found and jump to Footstep 8;
- Footstep 8: In case that forecast window is not reached, i.e., the twenty-four hours-ahead of wind power forecasting, jump to Footstep 2; else, jump to Footstep 9;
- Footstep 9; Organize the resulted forecasting results obtained in previous iteration in order to create the final twenty-four hours-ahead wind power forecasting windows;
- Footstep 10: Use the inverse wavelet transform to include the saved analysis smoothed in the Footstep 2;
- Footstep 11: Start the Monte Carlo simulation analysis; design the results outputs and end.

C. *Wind Power Forecasting Validation*

In order to have empirical results to carry out the fair and comparative analysis with other available forecasting approaches considering the same wind power historical data, several point forecast error criterion were used.

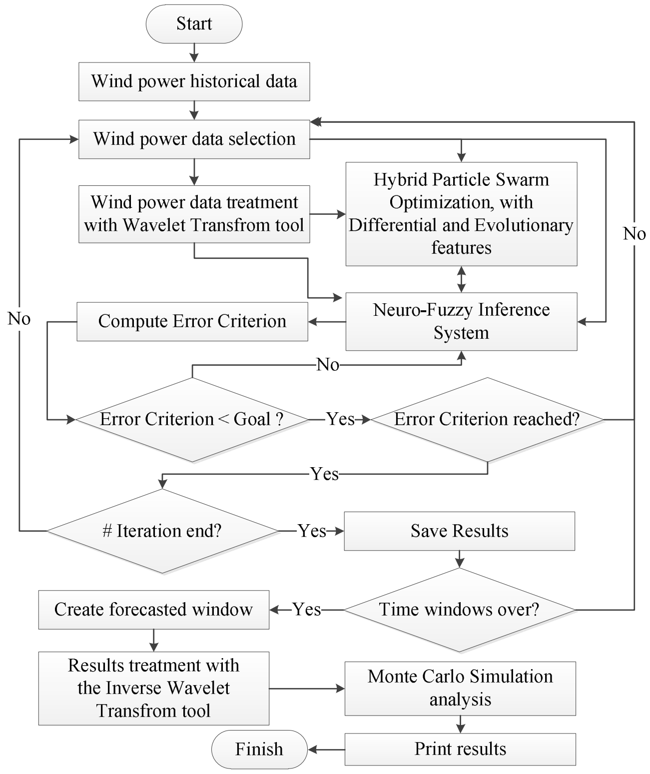

Fig. 1. The proposed EHWPF flowchart model.

TABLE I. THE PROPOSED EHWPF PARAMETERS DATA.

Tool	Parameters	Value
Wavelet Transform	Wavelet direction	"*row*"
	Decomposition Level	3
	Mother function	"*Db3*"
	Tool noise analysis	"*minimaxi*"
	Rescaling threshold	"*sln*"
Hybrid Particle Swarm Optimization, with Differential and Evolutionary features	Sharing information	0.5
	Start inertia	0.6
	Finish inertia	0.1
	Memory	1
	Cooperation	1
	Acceleration	1
	Swarm size	12
	Minimum location	"min. input"
	Maximum location	"max. input"
	Learning	0.1
	Internal iteration	50
Adaptive Neuro-Fuzzy Inference System	Membership function	9
	Internal iteration	45
	Membership function	"*trimf*"
EHWPF	Global number of Iteration	8

To this end, the mean absolute percentage error (MAPE) criterion is used. Also, the daily normalized mean average error (NMAE) and daily error variance criterions were used. The MAPE criterion is:

$$MAPE = \frac{100}{N} \times \sum_{n=1}^{N} \frac{\left|\hat{P}_{wn} - P_{wn}\right|}{\bar{P}_w} \quad (1)$$

$$\bar{P}_w = \frac{1}{N} \times \sum_{n=1}^{N} P_{wn} \quad (2)$$

where $\hat{P}_{wn}$ is the forecasted output at time n, P_{wn} is the historical wind power at time n, $\bar{P}_w$ is the rate mean value for the output time horizon, and N is the size rate of experimental of period ($N = 96$). Considering the previous details, the Daily Error Variance is described as:

$$\sigma_{wn}^2 = \frac{1}{N} \times \sum_{n=1}^{N} \left(\frac{\left|\hat{P}_{wn} - P_{wn}\right|}{\bar{P}_w} - e_{wn} \right)^2 \quad (3)$$

$$e_{wn} = \frac{1}{N} \times \sum_{n=1}^{N} \frac{\left|\hat{P}_{wn} - P_{wn}\right|}{\bar{P}_w} \quad (4)$$

For the NMAE criterion, the wind power installed considered was $P_{w_{intalled}} = 2700$ MW:

$$MMAE = \frac{100}{N} \times \sum_{n=1}^{N} \frac{\left|\hat{P}_{wn} - P_{wn}\right|}{P_{w_{installed}}} \quad (5)$$

III. CASE STUDY AND ANALYSIS OF RESULTS

The EHWPF approach was adapted to forecast the wind power for three hours-ahead with a time-step of fifteen minutes until complete a whole period of twenty-four hours ahead (short-term forecasting).

To this end, the historical wind power data considered was the same as described in [14] and available in [15]. The historical wind power data considered the different seasons of the year 2007 and 2008.

To carry out a just, effective and fair analysis, only the wind power records are used, for similar purposes as described in previous sections, and with approaches that have used the same data. The proposed EHWPF approach was implemented on a typical PC dotted with a Processor i5-6300U, @2.4GHz, and 4GB of RAM, running the Win10 and with MATLAB®2013b tool installed.

Moreover, the wavelet transform tool and the neuro-fuzzy inference system considered in this work are based on MATLAB toolboxes, while hybrid particle swarm optimization, with differential and evolutionary features, was designed from the beginning in MATLAB considering the material offered in [16] and the Monte Carlo simulation tool considering the directions provided in [17].

Table II provides the overall numerical results from the MAPE criterion obtained from the proposed EHWPF approach. The comparison results are supported by the information provided in [14]. It is possible to observe that, excluding the Summer day, the proposed EHWPF approach overpassed the previous forecasting approaches, evidencing an augmented precision.

TABLE II. EHWPF FORECASTING ERRORS CONSIDERING MAPE CRITERION.

Approach	Winter	Spring	Summer	Fall	Average
Neural Network	9.51	9.92	6.34	3.26	7.26
Wavelet Transform and Adaptive Neuro-Fuzzy	8.34	7.71	4.81	3.07	5.99
Hybrid Evolutionary Approach	5.74	3.49	3.13	2.62	3.75
Hybrid Wind Power Differential Approach	5.08	3.19	2.96	2.27	3.37
Proposed EHWPF Approach	2.61	3.11	2.98	2.08	2.70

TABLE IV. EHWPF FORECASTING ERRORS CONSIDERING NMAE CRITERION.

Approach	Winter	Spring	Summer	Fall	Average
Neural Network	5.22	3.72	2.35	2.15	3.36
Wavelet Transform and Adaptive Neuro-Fuzzy	4.58	2.89	1.78	2.03	2.82
Hybrid Evolutionary Approach	2.73	1.48	0.74	1.10	1.51
Hybrid Wind Power Differential Approach	0.94	0.49	0.28	0.39	0.53
Proposed EHWPF Approach	0.58	0.48	0.28	0.35	0.42

Table III provides the overall numerical results considering the Daily Error Variance from the proposed EHWPF approach. Again, the comparison results are supported from the information provided in [14]. It is possible to observe that, excluding the Fall day, the proposed EHWPF approach keeps some stability form its ancestor approach, i.e., the Hybrid Wind Power Differential Approach, however, with more positive pieces of evidence from the Winter day, which shows more accuracy on the results obtained.

Table IV provides the overall numerical results considering the NMAE criterion obtained from the proposed EHWPF approach, supported by the information provided in [14]. It is possible to observe that in general, the proposed EHWPF approach determines with more robustness the expected wind power, i.e., it shows how much wind power, on average is not forecasted.

Figures 2-5 shows the graphical results obtained considering the proposed EHWPF approach considering the representative days of each season of the year. As observed in Figure 2, the behavior of the forecasted result follows, in general, the real data, however, with some random disturbance. Also, from Figure 2 it is observed that in some moments the forecasted results is out from the Monte Carlo simulation results (gray gradient area). Such behavior is due to the reduced input data that was considered to perform the analysis and this sense the expected variance along the forecasted period is reduced.

TABLE III. EHWPF FORECASTING ERRORS CONSIDERING DAILY ERROR VARIANCE CRITERION.

Approach	Winter	Spring	Summer	Fall	Average
Neural Network	0.0044	0.0106	0.0043	0.0010	0.0051
Wavelet Transform and Adaptive Neuro-Fuzzy	0.0046	0.0051	0.0021	0.0011	0.0032
Hybrid Evolutionary Approach	0.0019	0.0015	0.0010	0.0008	0.0013
Hybrid Wind Power Differential Approach	0.0017	0.0016	0.0007	0.0006	0.0012
Proposed EHWPF Approach	0.0010	0.0017	0.0006	0.0007	0.0010

In Figure 3 it is possible to observe that even in the sudden and abrupt ramping of wind power data, the forecasting approach follows successfully the behavior in comparison with the real data. Similarly, as happened in Figures 1 and 2, Figures 3 and 4, in general, the results are well acceptable, accordingly with the reduced data considered for the analysis, even when the forecasted results are not in trend with the Monte Carlo simulation behavior.

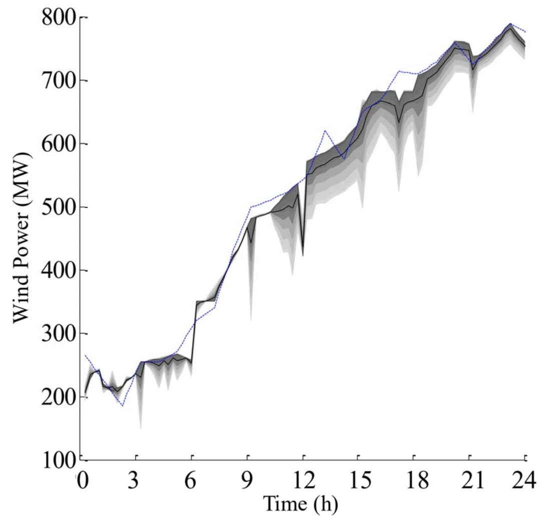

Fig. 2. Forecasted Winter day (black line real, blue line forecasted data).

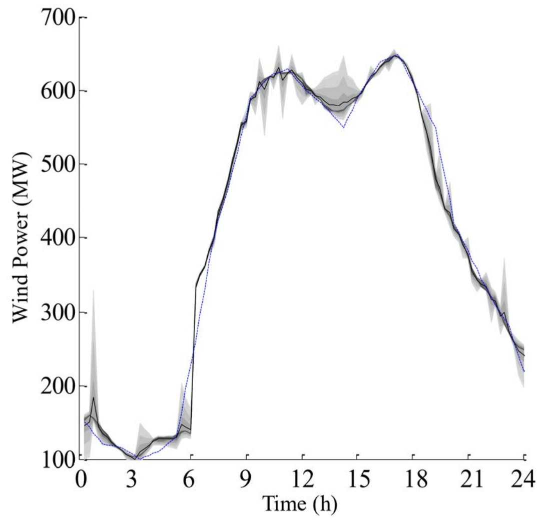

Fig. 3. Forecasted Spring day (black line real, blue line forecasted data).

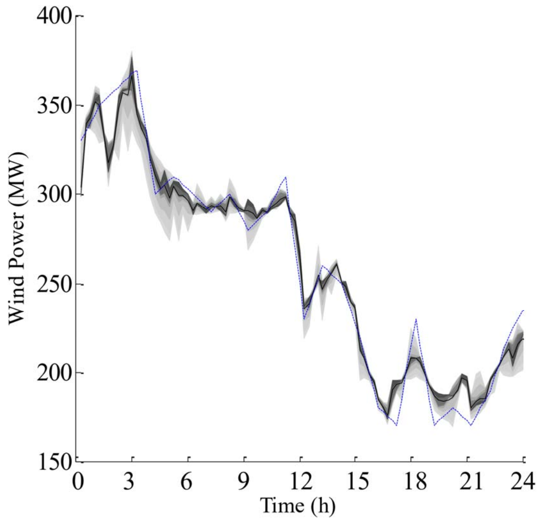

Fig. 4. Forecasted Summer day (black line real, blue line forecasted data).

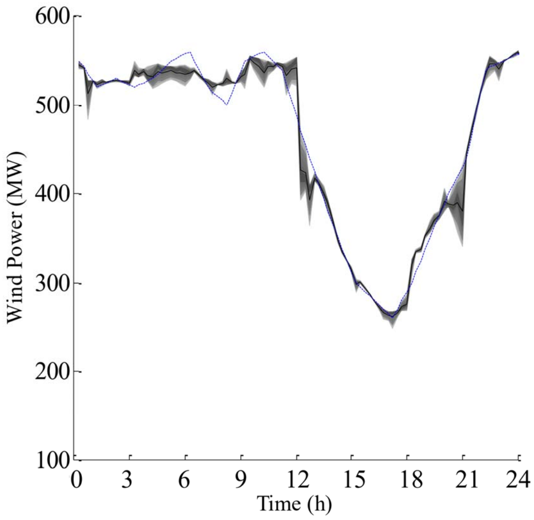

Fig. 5. Forecasted Fall day (black line real, blue line forecasted data).

Another reason that can create the disturbances observed is related to the Wavelet Transform tuning (on the beginning of the forecasting process and later when is created the transformed result), which may add some variability behavior on the forecasted result. All the forecasting results were provided in less than two minutes, on average, which is acceptable.

IV. CONCLUSION

In this work, an extended hybrid wind power forecasting, called EHWPF was presented, resulting from a successful combination of well-known tools and undergoing an improvement from its original goal. The proposed EHWP approach was tested and compared with other validated approaches considering the real wind power historical data in all the approaches for a fair and comparable comparison. The subsequent outcomes from this work are linked to the reduced output errors achieved and considering an acceptable time to get the output results, i.e., less than two minutes on average. The MAPE criterion was 2.70%, while the Daily Error Variance and NMAE criterions were on average 0.0010 and 0.42, respectively. Hence, the results show a encouraging trade-off between computational time, accuracy and response. In a general sense, the model can be even further explored considering other time-windows and a more extensive input data in order to increase the analysis behavior on the expected wind power forecast trend. Also, it is important to note that another extension of this work is related to an automated way that should be implemented to find the best input candidates, which is important for real-life applications.

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