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A Novel Fuzzy Multi-Objective Framework to Construct Optimal Prediction Intervals for Wind Power Forecast

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***Abstract*— The forecasting behavior of the high volatile and unpredictable wind power energy has always been a challenging issue in the power engineering area. In this regard, this paper proposes a new multi-objective framework based on fuzzy idea to construct optimal prediction intervals (PIs) to forecast wind power generation more sufficiently. The proposed method makes it possible to satisfy both the PI coverage probability (PICP) and PI normalized average width (PINAW), simultaneously. In order to model the stochastic and nonlinear behavior of the wind power samples, the idea of lower upper bound estimation (LUBE) method is used here. Regarding the optimization tool, an improved version of particle swam optimization (PSO) is proposed. In order to see the feasibility and satisfying performance of the proposed method, the practical data of a wind farm in Australia is used as the case study.**

Keywords*— interactive fuzzy satisfying method; combined LUBE; wind power forecast; uncertainty

I. INTRODUCTION

In recent years, the use of renewable energy sources (RESs) has become popular especially as the result of some useful characteristics such as cleanness, nearness to the consumers, modularity, etc [1]. Using these new RESs in the power systems has resulted in some significant improvements such as reducing power losses [2] and the system costs [3], increasing the power quality of the electrical services [4] and enhancing the reliability of the system [5] effectively. One of the most popular types of RESs is wind energy. Wind energy as an easy access source of energy in most of the areas has attracted the attention of many researchers in recent years [6]. Nevertheless, one significant issue regarding the use of wind energy is its volatile characteristic which makes accurate wind speed forecasting process a tedious and hard work [7]. In order to solve this problem, in recent years many different forecasting models are introduced. Most of these methods have tried to suggest more sufficient forecasting models which can track the wind speed/power samples more accurately [8]. But it is demonstrated in the literature that wind power forecast error can not be avoided even with the use of the most accurate forecasting models [9]. The output result of this conclusion has been a shift from the deterministic point forecast to the probabilistic uncertain forecast [10]. In this regard, many researches have been implemented in recent years which some of them can be named as quantile regression [11], fuzzy set theory [12], logit normal distribution [13] and quantile regression method [14].

In a general classification, the forecasting models can be categorized in two main groups [10]: 1) statistical models and 2) artificial intelligence based models. In the first group, regression models (linear or piecewise-linear) [15], Kalman filter [16], time series [17], data mining methods [18] and state space techniques [19] are famous. While these methods have been the first models in the forecasting area, but their usage for the new complex and nonlinear data such as wind power samples is limited. In the second group, artificial based approaches exist which can be named as expert systems [20], fuzzy systems [21], neural networks (NNs) [22] and neuro-fuzzy systems [23].

The second group has found more popularity especially as the result of their high capability for modeling nonlinear mappings. However, as mentioned before, there are always some degrees of error in the forecast data. The response to this challenge has been construction of prediction intervals (PIs). Each PI constructs a bandwidth which the forecast point will fall in. Also a probability confidence level is defined which shows the percent of the forecast points that are in the PIs. Some of the most outstanding works in this area can be named bootstrap-based PIs [24], mean-variance estimation method [25], optimal PIs [26] and lower upper bound estimation (LUBE) [27] method. Amongst these methods LUBE method has been the most promising

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solution since it can make PIs without any prejudgment about the distribution of the data samples. This issue is especially significant for wind power data which does not obey the normal distribution function.

According to the above discussions, this paper aims to use the LUBE method for construction of optimal PIs to forecast the wind turbine output power. The LUBE method uses a cost function to find the most optimal PIs with lowest average width. In fact, two significant criteria for construction of PIs are 1) PI coverage probability (PICP) and 2) PI normalized average width (PINAW). To date all the works have mixed these two targets to make a single-objective optimization method. However, in this work a fuzzy based approach is proposed to make a sufficient multi-objective framework to adjust the above two criteria suitably. Regarding the optimization process, particle swarm optimization (PSO) algorithm as a popular tool in this area is used. Also a sufficient modification is introduced for PSO algorithm to increase its search ability. The satisfying performance of the proposed method is examined on the practical data of a wind farm in Australia.

II. Proposed Multi-Objective LUBE Method

In order to make the LUBE model, a NN with two outputs are required to construct the upper and lower bounds. However, during the training of the NN, the upper and lower bounds are not available. Instead, a cost function is defined which should be optimized. The schematic diagram of this method is depicted in Fig. 1. As it was mentioned in the *Introduction* section, there are two main criteria for measuring a suitable PI: 1) PICP and 2) PINAW. By definition, PICP shows the percent of the forecast targets which have fallen in the bounds of the PI as follows:

$$PICP = \frac{1}{N}\sum_{t=1}^{N} c_t \tag{1}$$

$$c_t = \begin{cases} 1 & ; \; y_t \in [L_t, U_t] \\ 0 & ; \; y_t \notin [L_t, U_t] \end{cases} \tag{2}$$

where N is the number of samples, y_t is the forecast target and U_t and L_t are upper and lower bounds of the PI. Meanwhile a confidence level is defined which is used to accept or discard the relevant PI is discarded. The criterion for accepting the interval is that PICP is bigger than or equal to the confidence level.

The second criterion is PINAW. Too wide bounds for an interval are not useful in the forecasting targets while too narrow bounds will reduce the PICP value. Mathematically, PINAW can be calculated as follows:

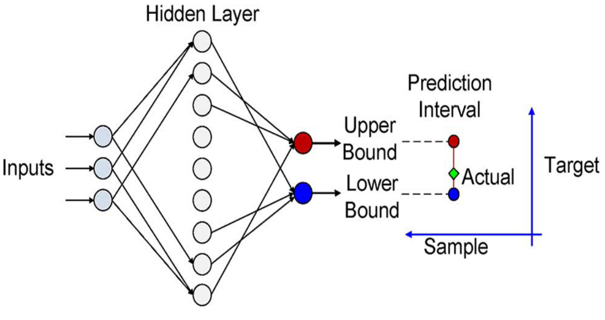

Fig. 1 Schematic diagram of LUBE method

$$PINAW = \frac{1}{NR}\sum_{t=1}^{N}(U_t - L_t) \tag{3}$$

where R is the range of the underlying targets used for normalizing PIs. This interactive relationship between the PICP and PINAW necessitates a useful framework for control of the quality of the intervals. In order to reach the suitable framework, we have designated two membership functions to the PICP and PINAW targets. The schematic of these membership functions are shown in Figs. 2 and 3. In these figures, μ_{PICP} and μ_{PINAW} are used to show the fuzzy membership functions of PICP and PINAW criterion, respectively. In order to reach an appropriate compromise between the optimization of these two targets, an interactive fuzzy satisfying solution is defined as follow:

$$F(X) = \min_{x\in\Omega}\left\{\max_{i=1,\dots,n}\left|\mu_{ref,i} - \mu_{f,i}(X)\right|\right\} \tag{4}$$

where n is the number of targets (here $n = 2$); $\mu_{f,i}$ is the membership function value of i^{th} target; Ω is the problem space; X is a vector including the NN weighting factors and $\mu_{ref,i}$ is the reference membership value for i^{th} target. The above formulation will let the decision maker to optimize both PICP and PINAW individually by adjusting the value of $\mu_{ref,i}$ for each of them. Generally, $\mu_{ref,i}$ is in the range [0,1].

III. Optimization Toll Based on Improved PSO (IPSO)

The PSO algorithm was first introduced by Kennedy and Eberhart in 1995 [28]. This algorithm mimics the behavior of birds or fishes to immigrate to far distances.

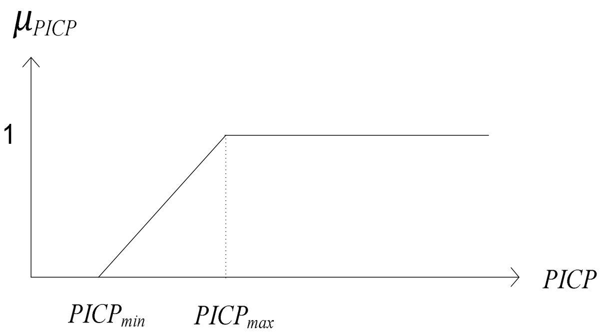

Fig. 2 Fuzzy membership function for PICP

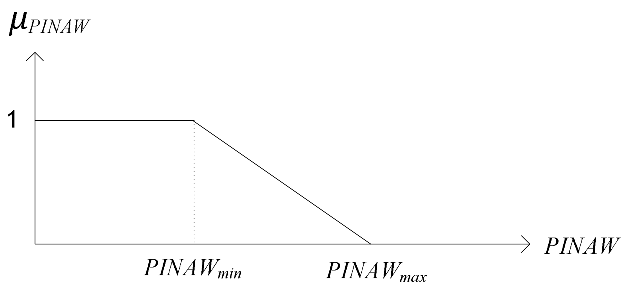

Fig. 3 Fuzzy membership function for PINAW

Some main characteristics of PSO algorithm can be named as 1) low adjusting parameters, 2) no need to derivative and 3) simple concept. The PSO algorithm performance greatly depends on the personal experience of the particles as well as the social experience of the total population.

Similar to the other evolutionary optimization techniques, PSO starts with a random population. Then the objective function is calculated for all the particles and the best particle is found (*gbest*). Now, the position of each particle should be updated. Meanwhile, the best experience of each particle is stored in a specific variable called $pbest_i$. For each firefly X_i, the below equations are computed to update its position:

$$Vel_i^{k+1} = \omega \times Vel_i^k + c_1 \times rand(.) \times (pbest_i - X_i^k) + c_2 \times rand(.) \times (gbest - X_i^k) \quad (5)$$

$$X_i^{k+1} = X_i^k + Vel_i^{k+1} \quad , \mathrm{i} = 1,2,...,N_{swarm} \quad (6)$$

where ω is the weighting factor, k is the iteration number, *rand* is a random number in the range of [0,1], c_1 and c_2 are the learning parameters; Vel_i^{k+1} is the velocity of i^{th} particle in k^{th} iteration and N_{swarm} is the number of swarms in the population.

After updating the position of all particles, the *gbest* and $pbest_i$ are updated. The best particle in *pbest* is supposed as the *gbest* for the next iteration. This process is repeated for several times until the termination criterion is satisfied. In order to improve the search ability of the PSO algorithm, a powerful modification method based on the crossover and mutation operators are also introduced (here called IPSO algorithm). The key idea behind this modification is to increase the diversity of the particles population and thus increasing the possibility of generating more optimal solutions. This improvisation stage is taken from the genetic algorithm. In this regard, in each iteration and for each particle X_i, three random solutions X_{m1}, X_{m2} and X_{m3} are selected from the swarm population such that $i \neq m1 \neq m2 \neq m3$. Then, using the mutation operator, the below test solution is produced:

$$\begin{aligned} X_{Test1} &= X_{m1} + \rho_1 \times (X_{m2} - X_{m3}) \\ X_{Test1} &= [x_{Test1,1}, x_{Test1,2}, ..., x_{Test1,d}] \end{aligned} \quad (8)$$

In addition, by the use of the crossover operator, two other test solutions are generated as follows:

$$\begin{aligned} x_{Test2,j} &= \begin{cases} x_{best,i}\,, & \text{if } \rho_2 \leq \rho_3 \\ x_i\,, & \text{otherwise} \end{cases} \\ x_{Test3,j} &= \begin{cases} x_{best,i}\,, & \text{if } \rho_3 \leq \rho_4 \\ x_{Test1,i}\,, & \text{otherwise} \end{cases} \end{aligned} \quad (9)$$

In the above equation, ρ_1 to ρ_4 are random values in the range [0,1]. The best solution among X_{Test1}, X_{Test2} and X_{Test3} is compared with X_i. If it is better than X_i then replaces it.

IV. Simulation Results

This part makes use of the practical dataset of the Starfish Hill Wind Farm located near Cape Jervis on the Fleurieu Peninsula. This wind farm is the first wind site in the south of Australia. Eight turbines are located on Starfish Hill and 15 on Salt Creek Hill [29]. The forecast time horizon is 15 minutes with the confidence level of 90%. The best structure of NN for construction of PIs is found using the partial autocorrelation method. The NN has 1 hidden layer with 7 neurons, experimentally. For the proposed IPSO algorithm, 30 particles are supposed and the termination criterion is to reach 200 iterations. The values of ω, c_1 and c_2 are chosen 1.4, 0.8 and 0.8 experimentally.

The simulations are implemented to show three main targets: 1) the satisfying performance of the proposed IPSO algorithm to optimize the fuzzy cost function, 2) the applicability of the proposed cost function and 3) the high accuracy of the LUBE forecasting model. In order to demonstrate the first target, the performance of proposed IPSO algorithm is compared with that of the original PSO algorithm. The simulation results for optimizing the proposed fuzzy cost function is shown in Table I. Here equal values are considered for the reference memberships. As it can be seen from Table I, the proposed method has satisfied both PICP and PINAW appropriately. From the optimization view, the proposed IPSO has also shown superior performance than the original PSO algorithm (less membership function value). According to Table I, the proposed IPSO algorithm has reached to higher PICP and lower PINAW values which show more its superior search ability than original PSO.

In the second part of the simulations, the high efficiency of the proposed cost function is shown. In this way and in order to see the effect of changing the values of reference memberships on the final solution, the results of considering five different preferences of ($\mu_{ref,1}$=1, $\mu_{ref,2}$=1), ($\mu_{ref,1}$=1, $\mu_{ref,2}$=0.9), ($\mu_{ref,1}$=0.9, $\mu_{ref,2}$=1), ($\mu_{ref,1}$=1, $\mu_{ref,2}$=0.8) and ($\mu_{ref,1}$=0.8, $\mu_{ref,2}$=1) are shown in Table II. According to this table, changing the values of the reference membership can affect the satisfying degree of PICP and PINAW targets directly. This full control on the values of these two objectives can provide a useful tool for the operator to apply his/her preferences effectively. In comparison with the traditional cost functions that are discussed in the literature [27], this useful idea for control of the PICP and PINAW objectives can provide more authority for decision maker. It is worth noting that the three operating points which are shown in Table II are all acceptable. In fact, all these five forecasting models have met the confidence level of 90% and thus it depends to the operator decision to choose the best one.

In order to show the high forecasting ability of the proposed LUBE method, Fig. 4 depicts the relative plot of the forecast upper bound (red curve), forecast lower bound (blue curve) and the real values of wind sample data (brown circles) through the optimization of the proposed fuzzy based framework. Note it that this plot is for the case of equal reference membership values, i.e. $\mu_{ref,1}$ = 1.0 , $\mu_{ref,2}$ = 1.0.

TABLE I
RESULTS OF OPTIMIZING OF THE PROPOSED FUZZY COST FUNCTION

Algorithm	PICP	PINAW	Membership Function value
PSO	87.9943	38.0039	0.1765390
Proposed IPSO	91.4882	35.9473	0.1472777

TABLE II

RESULTS OF OPTIMIZING THE PROPOSED COST FUNCTION FOR REFERENCE MEMBERSHIP

Case	Reference Membership Value	PICP	PINAW
1	$\mu_{ref,1} = 1.0$, $\mu_{ref,2} = 1.0$	91.68433	35.477322
2	$\mu_{ref,1} = 1.0$, $\mu_{ref,2} = 0.9$	92.00127	36.245390
3	$\mu_{ref,1} = 0.9$, $\mu_{ref,2} = 1.0$	90.88436	32.496512
4	$\mu_{ref,1} = 1.0$, $\mu_{ref,2} = 0.8$	93.49924	37.947386
5	$\mu_{ref,1} = 0.8$, $\mu_{ref,2} = 1.0$	89.88403	31.094241

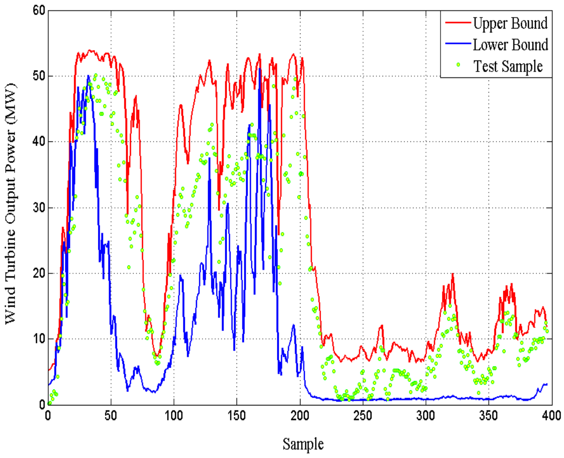

Fig. 4 Optimal PIs for wind power test data using the proposed fuzzy based framework

As it can be seen, the forecast points are in the range of the forecast PIs suitably. It should be considered that the high variation of the wind turbine output power in Fig. 4 from 0 to 50 MW shows the high complexity and nonlinearity of the data samples for the forecasting purposes. Nevertheless, the proposed method has forecasted the wind power samples, successfully. These variations for the first 200 samples are more severe than the rest. Using optimal PIs for forecasting the wind power samples can help the optimal operation and management of the power systems effectively. Without an accurate estimation of the wind turbine output power, a part of the electric consumers may not be supplied or at least are supplied with low quality electrical services. Using the proposed LUBE method can give a good estimation of the output variations of the wind turbine.

V. CONCLUSION

This paper proposed a new fuzzy based cost function for optimizing the LUBE method to construct more optimal PIs with more controllability. In this regard, according to the nature of the problem, new membership functions were suggested for PICP and PINAW objectives. Also, a sufficient min-max approach was suggested to convert the multi-objective optimization framework into its equivalent single-objective optimization framework. In order to search the problem space deeply, a new improved algorithm called IPSO was proposed too. This algorithm is equipped with one mutation and two crossover operators to increase the diversity of the particles. The simulation results on the practical data of wind farm showed the high performance and suitability of the proposed method for forecasting wind turbine output power. Also, it was seen that the proposed fuzzy based framework can give more authority to the operator for applying his/her preferences to the system. From the optimization view, the usefulness of the modification method for increasing the ability of the PSO algorithm to optimize the proposed fuzzy cost function was demonstrated too.

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