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# An optimized mean variance estimation method for uncertainty quantification of wind power forecasts

Abbas Khosravi *, Saeid Nahavandi

*Centre for Intelligent Systems Research (CISR), Deakin University, Waurn Ponds Campus, Locked Bag 20000, Geelong, Victoria 3220, Australia*

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ABSTRACT

A statistical optimized technique for rapid development of reliable prediction intervals (PIs) is presented in this study. The mean–variance estimation (MVE) technique is employed here for quantification of uncertainties related with wind power predictions. In this method, two separate neural network models are used for estimation of wind power generation and its variance. A novel PI-based training algorithm is also presented to enhance the performance of the MVE method and improve the quality of PIs. For an in-depth analysis, comprehensive experiments are conducted with seasonal datasets taken from three geographically dispersed wind farms in Australia. Five confidence levels of PIs are between 50% and 90%. Obtained results show while both traditional and optimized PIs are hypothetically valid, the optimized PIs are much more informative than the traditional MVE PIs. The informativeness of these PIs paves the way for their application in trouble-free operation and smooth integration of wind farms into energy systems.



## Introduction

Wind power forecasting with a forecast horizon of a few minutes ahead is essential for trouble free operation of energy networks with a high level of wind power penetration [1]. Tasks such as provision of reserves, security and stability of system, and operation of wind farms require short-term wind power forecasts [2,3]. Forecasts are also used by system operators, schedulers, and network managers.

A myriad of academic studies has been undertaken dealing with the problem of wind power forecasting. Methods used for wind power forecasting can be classified into two main groups, physical and statistical [4,5]. Physical models, also called numerical weather prediction, utilize meteorological and topological information to determine the speed and direction of wind in a specific region. Statistical methods, also referred to as data-driven methods, mainly use historical wind power data to forecast the future power outputs. It has already been shown that statistical methods are more appropriate for short-term forecasting rather than long-term forecasting [4]. Ensemble methods can also be used for wind power forecasting [6], where agreement between models can be considered as a sign of forecast certainty. A framework for skill forecasting based on wind power ensemble forecasts is also proposed in [7]. Associated uncertainties are effectively handled using prediction risk indices defined based on the ensemble forecast. A review on the state-of-the-art methods for wind power prediction and forecasting is provided in [5,8,9].

The majority of linear and nonlinear regression methods existing in the current literature can be applied as a statistical model for wind farm power forecasting. However, time series regression models [10] and neural network (NN) models [11] have been widely applied in literature. Implementation ease and being computationally less intensive than physical models are the main reasons for their popularity.

The forecast accuracy of wind power has gradually improved through developing more advanced methods and taking advantage of the availability of cheap computational power. Despite these progresses, there are many cases that forecast errors are large and cannot be fully eliminated [12,13]. For the case of large penetration of wind farms into the energy market, even small forecasting errors may easily jeopardize the energy system operation. From a system operator's perspective, it is essential to have an indication of the forecast accuracies. This indication can be used as a measure to check the level of uncertainties affecting forecasts. If large, forecasts are highly likely unreliable and should be investigated with more care. If small, operational decisions can be reached with more confidence using point forecasts. So, appropriately quantifying uncertainties connected to wind power generation forecasts is of

* Corresponding author. Tel.: +61 352272507.
*E-mail addresses:* abbas.khosravi@deakin.edu.au (A. Khosravi), saeid.nahavandi@deakin.edu.au (S. Nahavandi).

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paramount importance [2,14]. This is a prerequisite for their trouble free integration into the grid in large penetration scenarios.

As indicated in [15], recent studies in the field of wind energy forecasting have been shaped towards probabilistic methods. Of particular interest are methods for construction of prediction intervals (PIs). PIs can properly quantify uncertainties associated with forecasts generated by models. PIs are constructed with a preset probability known as the confidence level, $(1-\alpha)\%$. PIs are an assisting tool in quantification of uncertainties associated with the point forecasts. The width of valid PIs provides valuable information about the level of uncertainties affecting point forecasts.

A generic nonparametric method has been proposed in [13] to develop wind power PIs. The proposed method uses a fuzzy inference system that defines the distribution of forecast errors. Also another method is proposed in [16] where intervals are squeezed in the case of stable weather conditions. A general parametric method for construction of PIs from any arbitrary continuous distribution is also presented in [17].

The delta technique [18], the bootstrap method [19], the Bayesian method [20], the lower upper bound estimation technique [21], and the mean–variance estimation (MVE) method [22] are NN-based methods proposed in literature for developing PIs. Hybrid methods have also been recently proposed for construction of optimized PIs [23–25]. Each method has its own advantages and disadvantages, such as making especial assumption about data distribution or computational requirements. A comparative review of these methods using different case studies is provided in [26,27].

This study focuses on constructing PIs using the MVE technique. Being computationally less demanding than other methods is the main motivation for hiring this method in this study. The MVE method trains a NN model to approximate the variance of targets. Conditioning the target variance on the set of NN model inputs allows the analysts to approximate the case-dependant variance and then quantify uncertainties associated with forecasts through construction of PIs.

The main contribution of this study is twofold.

- First, a reliable NN method for PI construction is extended to renewable energy field. This extension allows us to quantify uncertainties associates with wind power forecasts.
- Second, it provides a systematic way to improve the calibration and sharpness of PIs. Instead of training using minimization of error-based cost functions, the proposed method hires a PI-based cost function for of adjusting NN parameters. Different seasonal data sets are used for conducting experiments and drawing conclusions. Five confidence levels (50–90%.) are considered for developing PIs. Method performance, the confidence level effects, and validity (calibration) and informativeness (sharpness) of PIs are comprehensively discussed when evaluating results obtained using original and optimized MVE method.

The next section briefly describes the MVE method. Performance measures used for quantitative assessment of PIs are introduced in section 'Quantitative evaluation of PIs'. Section 'PI optimization' provides the details of the optimized MVE method. Section 'Experiments and results' demonstrates the simulation results. Conclusions are given in section 'Conclusion'.

## Mean variance estimation technique

Nix and Weigend [22] introduced the MVE technique to directly construct PIs using two NN models. Considering a normal distribution for forecast errors around the true target mean, $y$, is the main assumption of this technique. As per this, accurate estimation of the mean and variance values of this distribution paves the way for PI construction. A dedicated NN is considered by this method to estimate the variance of targets, which can be either homogenous or heteroscedastic. This method handles non-uniform and input dependent residuals and captures the local volatility of the targets. Simplicity, ease of implementation and its flexible structure are the key advantages of this method. In contrast to Bayesian and delta method, calculation of time-consuming matrix derivatives is not required for construction of PIs. Proper selection of inputs and considering a bigger size $NN_\sigma$ allows the analyst to effectively and efficiently approximate a nonstationary variance.

Fig. 1 displays the steps of the MVE method. NN inputs, indicated as $x$, can be identical or different. NN structures can be freely determined as per data nonlinear patterns and experiment requirements. The neuron in the output layer of $\hat{\sigma}^2$ is an exponential function resulting in strictly positive variance estimation. Assuming that $NN_y$ precisely estimates $y(x)$, the approximated PIs with a $(1-\alpha)\%$ confidence level are,

$$\hat{y}(x, w_y) \pm z_{1-\frac{\alpha}{2}}\sqrt{\hat{\sigma}^2(x, w_\sigma)} \tag{1}$$

where $w_y$ and $w_\sigma$ are NN parameters to estimate $\hat{y}$ and $\hat{\sigma}^2$ respectively. It is important to note that the variance of targets, $\sigma_i$, is unknown a priori. Therefore, supervised learning methods cannot be applied for adjusting parameters of $NN_\sigma$. Instead, a maximum likelihood estimation method is employed to adjust NN parameters. It is assumed that forecasting errors come from a normal distribution. As per this, the data conditional distribution is,

$$P(t_i|x_i, NN_y, NN_\sigma) = \frac{1}{\sqrt{2\pi\hat{\sigma}_i^2}} e^{-\frac{(t_i-\hat{y}_i)^2}{2\hat{\sigma}_i^2}} \tag{2}$$

Taking the natural logarithm of (2) and discarding fixed value terms leads to,

$$C_{MVE} = \frac{1}{2}\sum_{i=1}^{n}\left[ln(\hat{\sigma}_i^2) + \frac{(t_i-\hat{y}_i)^2}{\hat{\sigma}_i^2}\right] \tag{3}$$

Using (3) as a cost function, a three step training method was introduced in [22] for tuning of $w_y$ and $w_\sigma$. In this method, we first split available samples into two training sets called $D_1$ and $D_2$. In Phase I, $NN_y$ is trained to predict $y_i$. Parameter tuning is performed through minimization of a traditional error-based cost function for samples in $D_1$. Samples in $D_2$ can be used as the validation set to obtain a NN with a proper generalization power. In Phase II, parameters of $NN_y$ are left to be fixed, and samples in $D_2$ are applied for training $NN_\sigma$. Proper tuning of $w_\sigma$ is done through minimization of the cost function described in (3). $NN_y$ and $NN_\sigma$ are employed to predict $y_i$

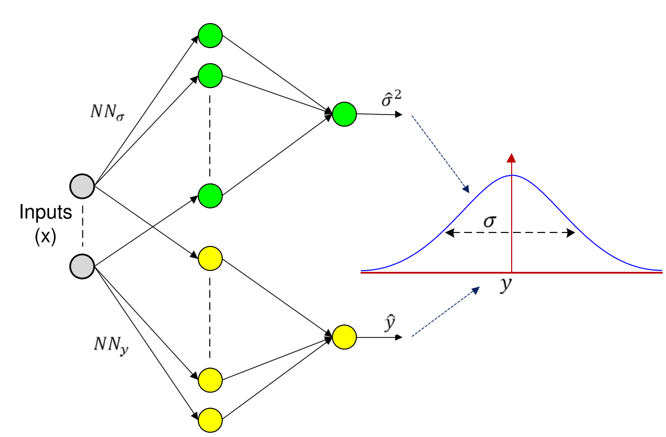


**Fig. 1.** A schematic of the mean–variance estimation method for construction of PIs.