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# A study of single multiplicative neuron model with nonlinear filters for hourly wind speed prediction

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ABSTRACT

Wind speed prediction is one important methods to guarantee the wind energy integrated into the whole power system smoothly. However, wind power has a non–schedulable nature due to the strong stochastic nature and dynamic uncertainty nature of wind speed. Therefore, wind speed prediction is an indispensable requirement for power system operators. Two new approaches for hourly wind speed prediction are developed in this study by integrating the single multiplicative neuron model and the iterated nonlinear filters for updating the wind speed sequence accurately. In the presented methods, a nonlinear state–space model is first formed based on the single multiplicative neuron model and then the iterated nonlinear filters are employed to perform dynamic state estimation on wind speed sequence with stochastic uncertainty. The suggested approaches are demonstrated using three cases wind speed data and are compared with autoregressive moving average, artificial neural network, kernel ridge regression based residual active learning and single multiplicative neuron model methods. Three types of prediction errors, mean absolute error improvement ratio and running time are employed for different models' performance comparison. Comparison results from Tables 1–3 indicate that the presented strategies have much better performance for hourly wind speed prediction than other technologies.


## 1. Introduction

In recent years, the world has been turning to the alternatives of fossil fuels for a cleaner and economical energy society [1,2]. Wind energy conversion systems have been drawing attention as a clean electricity source [3,4]. Efficient and stable utilization of the wind energy is an important issue in this context [5]. Specially, accurate wind speed estimation of the trend and persistency is critical towards optimizing the selection of wind farm cites and planning of wind power generation [6,7]. However, the intermittency, non–stationary and stochastic uncertainty of wind speed poses great challenges as to the reliable and efficient production of wind power [8]. Therefore, the development of efficient modeling tools is necessary to overcome the above technical challenges for accurate wind speed prediction and is vital to optimize the efficiency of wind power generation.

The wind speed prediction methods can be classified into four classes: the physical model, the conventional statistical model, the spatial correlation model, and the artificial intelligence and other new methods [9]. Physical models need more parameters, they are good at long–term calculation and are applied in weather prediction [10,11]. Statistical models are popular in practice because of their simple computation [12–15]. As for spatial correlation methods, they use multi–dimensional data from different measurement stations to predict the future wind speed [16]. In artificial intelligent models, ANNs (artificial neural networks) are popular due to their good nonlinear performance. Celik and Kolhe [17] employed an ANN model to predict wind speed probability density distribution by using the Weibull function's parameters as

*Abbreviations:* SMN, Single multiplicative neuron; ARMA, Autoregressive moving average; ANN, Artificial neural network; KRR, Kernel ridge regression; ARIMA, Autoregressive integrated moving average; SVR, Support vector regression; UKF, Unscented Kalman filter; IEKF, Iterated extended Kalman filter; IUKF, Iterated unscented Kalman filter; RSAL, Residual active learning; AMSE, Average mean square error; RMSE, The root mean square error; MAPE, Mean absolute percentage error; MAE, Mean absolute error; IR, Improvement ratio.

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inputs. Based on ARIMA (autoregressive integrated moving average) model, ANN and Kalman Filter, two hybrid methods, including the ARIMA–ANN model and the ARIMA–Kalman model, were proposed and their performance was compared in Liu et al. [18]. Velo et al. [19] suggested an ANN model for wind speed estimation. One ANN model with particle swarm optimization based optimal parameters selection was provided for wind speed prediction in Ref. [20]. Bouzgou and Benoudjit [21] presented an approach for wind speed prediction based on the multiple architecture system, which was composed of multiple linear regression, ANN and SVR (support vector regression). With the basis of wavelet theory, wavelet packet, ARIMA and ANNs, three hybrid models were proposed to predict the wind speed in Liu et al. [22]. In addition to ANN models, SVR methods have been applied to predict wind speed through a nonlinear kernel function based predictive model within high–dimensional feature space. Douak et al. [23] presented three active learning methods to construct the training set applied to wind speed prediction based on the kernel ridge regression approach. An approach for long–term wind speed prediction was developed in Yu et al. [24] by integrating Gaussian mixture copula model and localized Gaussian process regression. Guo et al. [25] suggested a hybrid seasonal auto–regression integrated moving average and least square support vector machine model to predict the mean monthly wind speed in Hexi Corridor. The UKF (unscented Kalman filter) was integrated with SVR based state–space model to predict the wind speed sequence in Chen and Yu [26]. However, general ANNs and SVRs have desired characteristics such as optimal solution and generalization capability, but they do not have strong capacity to handle system uncertainty and stochastic nature [26].

Recently, as an alternative to general ANNs, the SMN (single multiplicative neuron) model with simple network structure and fast learning ability has been proposed [27,28], and it has been successfully applied to time series prediction [29,30]. In this article, two novel hybrid predictive modeling methods are developed by integrating the IEKF (iterated extended Kalman filter) [31] and the IUKF (iterated unscented Kalman filter) [32] with the SMN model based nonlinear state–space model to enhance the capacity of handling stochastic and dynamic uncertainty as well as minimize the errors of wind speed prediction. The nonlinear state–space model is formed based on the SMN model firstly and then the IEKF and the IUKF are employed to conduct iterative state estimation on the SMN model based nonlinear state–space model with strong stochastic uncertainty (they are shortened as the IEKF–based–SMN model and the IUKF–based–SMN model, respectively.). Finally, the wind speed sequence is predicted from the IEKF–based–SMN model and the IUKF–based–SMN model. In this way, the integrated approaches can reduce prediction errors by well accounting for the stochastic and dynamic nature of wind speed sequence.

The remainder of the article is organized as follows. In Section 2, the IEKF and the IUKF methods are integrated with the SMN model to form the novel IEKF–based–SMN model and the novel IUKF–based–SMN model for hourly wind speed prediction. The developed approaches are applied to wind speed prediction of three cases and their performance is compared with ARMA, ANN, KRR–RSAL, and SMN model techniques in Section 3. Conclusions and future research of this work are summarized in Section 4.

## 2. Prediction model

### *2.1. The single multiplicative neuron model based state–space model*

General ANNs can recognize hidden pattern or relationship in historical observations and use them to predict the future values, but the development of general ANNs has many difficulties such as the selection of inputs to network, the selection of network structure and the calculation of model parameters [33]. Recently, the SMN model has been proposed as an alternative to general ANNs. The SMN model derives its inspiration from the single neuron computation in neuroscience, and only the input connections need to be determined during the learning process. Therefore, the SMN model is much simpler in structure and lower in computational complexity than the general ANNs, and it is acknowledged that the SMN model can provide more efficient solutions to some problems. The basic architecture of SMN model which is used in this work is presented in Fig. 1, where $\omega_l$, $b_l$ and $u_l$ ($l = 1, \ldots, n$ and $n$ is the input vector dimension of SMN model.) are the weight, the biase and the input value of the SMN model. The multiplication node $z$ is transformed to the output function $y$ with the *logsig* function defined as follows.

$$y = \frac{1}{1+e^{-z}} \quad \left( z = \prod_{l=1}^{n} (\omega_l u_l + b_l) \right). \tag{1}$$

Compared with general ANNs, although the SMN model has advantages of better approximation capabilities, simpler network structures and faster learning ability, the development of SMN model may suffer from the basic limitation on estimation of the model parameters in the training stage. Online optimization of the weights and biases of SMN model is employed based on the nonlinear filters due to their strong capability of handling random fluctuations and uncertainty in wind speed in this paper. Assumed that the historical wind speed data are $\mathbf{y} = [y_1 \quad y_2 \quad \cdots]$ and at least the first $n$ wind speed data is known, so the input vector of the SMN model at instant $k$ is

$$\mathbf{u}_k = [y_{k-n} \quad y_{k-n+1} \quad \cdots \quad y_{k-1}] \quad (k \ge n+1). \tag{2}$$

In addition, let

$$\mathbf{x}_k = [\omega_{k,1} \quad \omega_{k,2} \quad \cdots \quad \omega_{k,n} \quad b_{k,1} \quad b_{k,2} \quad \cdots \quad b_{k,n}]^T \tag{3}$$

represent the state vector, then the state–space equations derived from the SMN model for wind speed prediction can be expressed as

$$\mathbf{x}_{k+1} = \mathbf{x}_k + \mathbf{v}_k, \tag{4}$$

$$y_k = \frac{1}{1+e^{-z_k}} = h(\mathbf{x}_k, \mathbf{u}_k) + \mathbf{w}_k, \tag{5}$$

where $\mathbf{v}_k$ is the process noise with covariance matrices $\mathbf{Q}_k$, $\mathbf{w}_k$ is the observation noise with covariance matrices $\mathbf{R}_k$, $y_k$ is the observation value of the dynamic model at instant $k$, and $h(\bullet, \bullet)$ is the nonlinear function of the state vector $\mathbf{x}_k$ and the input vector $\mathbf{u}_k$.

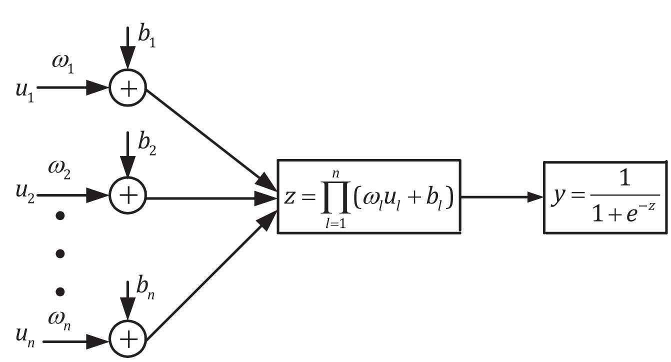


**Fig. 1.** The diagram of single multiplicative neuron model.