Short-term wind speed forecasting model based on ANN with statistical feature parameters

Christos S. Ioakimidis
ERA Chair 'Net-Zero Energy Efficiency on City Districts'
Research Institute for Energy, University of Mons
Mons, Belgium
christos.ioakeimidis@umons.ac.be

Panagiotis I. Dallas
Wireless Network Systems Division
INTRACOM Telecom S.A.
Athens, Greece
pdal@intracom.gr

Konstantinos N. Genikomsakis
DeustoTech Energy
Deusto Institute of Technology, University of Deusto
Bilbao, Spain
kostas.genikomsakis@deusto.es

Sergio Lopez
Department of Industrial Technologies
University of Deusto
Bilbao, Spain
sergio.lopez@deusto.es

***Abstract*—The intermittent and unstable nature of wind raises significant challenges for the operation of wind power systems, either residential installations or utility-scale implementations, necessitating the development of reliable and accurate wind power forecasting techniques. Given that wind speed forecasting is typically considered the intermediate step for wind power forecasting, the present work proposes a novel short-term wind speed forecasting model based on an artificial neural network (ANN), with the key characteristic that statistical feature parameters of wind speed, wind direction and ambient temperature are employed in order to reduce the input vector and thus the complexity of the model. The results obtained indicate that the proposed model strikes a reasonable balance between accuracy and computational requirements for a forecasting time horizon of 24 hours, providing a light-weight solution that can be integrated as part of energy management systems for small scale applications.**

Keywords*—*artificial neural network; smart house; statistical feature parameters; wind speed forecasting

I. Introduction

The pressing need over the years for security of energy supply as well as renewable and clean energy generation has accelerated, among others, the theoretical advances and applied developments in wind turbine technologies [1], [2]. Wind power has emerged as one of the most appealing renewable energy sources, resulting in the installation of an increasing number of wind turbines worldwide [3]. It is indicative that the average size of newly delivered wind turbines to the market in 2012 was 1.8 MW, against an average of 1.7 MW for 2011 [4]. The global wind power capacity reached approximately 282.5 GW by the end of 2012, with 45 GW of new capacity being installed during this year and reflecting a growth of 19% [5]. With the highest capacity of commercially available wind turbines currently at 7.5 MW, a number of companies are already working towards the development and implementation of larger size models. Meanwhile, recent years have also witnessed particular research interest for small wind turbines with rated power less than 200 kW [6], [7]. In support of this, the available data indicate that the industry of smaller wind turbines (<100 kW) is also promising [4], given that manufacturers offer nowadays advanced technology solutions for a range of applications, including residential or complex buildings, grid-connected or isolated systems.

In general, the evolution of residential electricity consumers into the so-called “prosumers” that have the ability to consume, produce and store electricity [8], requires radical changes in the structure and operation of the electricity grids. Therefore, the wider deployment of distributed energy resources (DERs) has triggered considerable research efforts for the integration of the decentralized generation units into the main grid [9], towards the realization of the smart grid vision [10].

In this direction, real-time monitoring and control over the electricity usage is considered to be beneficial even for residential electric utility customers, given that the average data available from monthly electricity bills are insufficient for energy management decisions [11]. This becomes more important in the case of a modern residence, or a “smart house”, where apart from consumption, electricity is generated from micro-renewable energy sources (microRES), e.g. residential wind turbines or solar photovoltaic (PV) panels, while electricity storage options may include a fixed battery and/or a battery of a plug-in electric vehicle that can be connected to the electric system of the “smart house” in order to exchange electricity bilaterally [12]. It follows that a number of energy management decisions arise in this case, e.g. charge/discharge the fixed and/or the EV batteries and buy/sell electricity from/to the grid. In this context, forecasting of the power output from the microRES within a certain time frame offers the opportunity for more efficient energy management decisions, e.g. scheduling the operation of the "smart" household appliances in the most beneficial time in order to maximize the profit for the "prosumer".

Given the dependence of wind turbine power output on wind speed, a typical approach in wind power forecasting consists in matching the forecasted wind speed values on the wind turbine power curve, as in [13]. A careful review of the relevant literature indicates that there is growing research interest on wind speed/power forecasting [14]-[16], which is considered to be a complex yet challenging problem [3] due to its high uncertainty, variability, and temporal and spatial dependency. More specifically, wind speed forecasting methods are typically divided into two broad categories, namely physics-based numerical weather prediction (NWP) models and data-driven approaches [13]. NWP models have been widely used to forecast global wind conditions and other meteorological parameters [17], but they are characterized by intrinsically high computational requirements. On the other hand, data-driven approaches are based on historical wind speed data and can be further divided into two groups, namely statistics-based methods and artificial intelligence-based models [13]. The former ones take advantage of the autoregressive behavior of the wind [18], however the forecasting accuracy decreases rapidly with the look-ahead time [19]. Typical examples include approaches based on time series [20], Kalman filtering [21], Markov chain models [22], and Bayesian methods [23]. For the latter group, an indicative list of computational intelligence techniques consists of artificial neural networks (ANNs) [24], fuzzy systems [25], and support vector machines (SVMs) [26]. Moreover, hybrid strategies that combine one or more of the aforementioned approaches are proposed in [27], [28].

The time horizon of wind speed forecasting algorithms depends on the application and typically ranges from a few seconds (very short-term forecasting) up to one week ahead (long-term forecasting). Relevant studies show that statistical methods generally outperform NWP-based models in terms of forecasting accuracy for the first four hours, whereas the latter ones are preferable for longer forecasting horizons [18]. Moreover, approaches that combine multiple computational intelligence techniques can effectively reduce the wind power forecasting errors [17]. In this context, significant research efforts are focused on methods for forecasting up to 24 h ahead to facilitate the integration of grid-connected wind farms under the distributed generation scheme as well as to optimize the control of stand-alone and hybrid systems.

Combining the above, the objective of this study is to develop an acceptably accurate wind speed forecasting tool as part of an energy management system for smart buildings using small low-cost autonomous devices, given that good wind speed and power forecasts are particularly important not only for reducing energy storage requirements and operation costs, but also for participating in the short-term electricity market. To this end, the present work proposes a short-term wind speed forecasting model for residential settings or small scale commercial applications, based on an ANN using statistical feature parameters in order to combine low computational complexity and input information requirements. Feeding the raw dataset from meteorological sensors in the model's input, without pre-processing as in typical ANN-based approaches, may have potentially substantial implications on the performance and generalization capability of the forecasting model, due to over-parameterization or over-fitting of the input data [29]. To overcome these shortcomings, the proposed model employs statistical feature parameters in the input vector, while the optimum structure of the ANN model is determined through cross-validation using a trial-and-error approach, as in [30], [31], for the case of forecasting of solar irradiance and photovoltaic (PV) power production.

The rest of this paper is organized as follows. Section II describes the development of the forecasting model, the results obtained are discussed in the subsequent section III, while Section IV outlines the main conclusions.

II. Methodology for Short-term Wind Speed Forecasting

A. Measurements and Data

For the purposes of this work, data were collected from the wind station located at the University of Deusto, Bilbao, Spain, covering the period from October 2010 to October 2011. The wind station collects data every 10 minutes in time series format and each measurement represents a sample of wind speed, wind direction and average temperature. Table I summarizes the main statistics of the relevant measurements.

B. Preliminary Analysis of Collected Data

A preliminary analysis of the collected data was conducted to identify the relations among parameters implicated in wind speed forecasting and thus determine which statistical feature parameters could be considered as potential inputs in the proposed model. Specifically, the measurements from the anemometer indicate that the highest variations of the wind speed during the year depend on the wind direction. Although the Spearman correlation between wind speed and direction is non-significant with a value of -0.3585, Fig. 1 shows that the highest speed values are collected in intervals centered at the direction angles 130° and 310°.

TABLE I. Summary Statistics

Measure	Wind speed (m/s)	Temperature (°C)	Wind direction (°)
Min	0.30	3.30	0
First quartile (Q1)	3.20	13.00	112
Median	5.90	16.70	134
Mean	7.05	17.39	176
Third quartile (Q3)	10.10	21.20	271
Max	26.40	39.50	359

After filtering and processing of the collected dataset, it may be observed that there is no correlation between wind speed and temperature, even though the analysis of the daily data reveals, as expected, that there is a moderate negative correlation between wind speed and increment of temperature during the night hours. In addition, a non-significant statistical correlation is observed between temperature and wind direction ($\rho_{Spearman}$=0.248, sig. 0.01). However, it is noted as a side observation that the temperature is lower when the wind comes from the north compared to the case of the wind blowing from the south, as shown in Fig. 2, where the boxplots represent the interquartile range of the temperature sample for each wind direction, after removing the outliers.

C. Input Parameters for ANN-based Forecasting Model

The main characteristic of the proposed ANN-based approach for forecasting of wind speed is the use of statistical feature parameters in the multilayer perceptron (MLP) model, as in [31]. To define the input vector, different statistical parameters from the main features are considered, namely wind speed, wind direction and temperature. At this point, it is important to note the following: a) the wind speed is stochastic and highly variable, b) to the authors' knowledge no mathematical models exist that could be used as a reference in order to introduce additional statistical parameters for this purpose, and c) the relationships between variables are relatively poor, as shown in the previous sub-section.

The initial analysis of the wind speed time series reveals the expected non-stationary behavior and thus suggests the use of the first order difference FOD as a possible parameter (Fig. 3). The first difference of a time series, denoted as $\nabla x_t = x_t - x_{t-1}$, eliminates the linear trend of the series. The maximum of the first difference of the wind speed, denoted as $FOD_{max} = \max\{\nabla x_t\}$, provides information about the variation of the wind speed during the day. Preliminary results with the use of this parameter only point to the fact that additional key statistical parameters from the wind speed could potentially improve the quality of the model.

The average of the wind speed W_{avg} and its standard deviation W_{std} in the last 24 h are included to determine the dispersion of the data in the sample used in relation to the sample mean. For the temperature parameter, the average T_{avg} of the last 24 h is used, given that the temperature variation between day and night hours in the region under study can be considered relatively low. The last feature employed is the wind direction angle, which has a large number of small variations during the day around more or less stable values. For this reason, the mode of the wind direction angle W_{dir} is used as a statistical parameter for the wind direction.

Summarizing, the forecasting factors used for determining the input vector I, defined in (1), consist of the average of the wind speed in the last 24 h, the standard deviation of the wind speed in the last 24 h, the maximum of the first order difference of the wind speed, the average of the temperature in the last 24 h, the mode of the wind direction in the last 24 h, and the day of the year $d \in [1,365]$.

$$I = \left[W_{avg}, W_{std}, FOD_{max}, T_{avg}, W_{dir}, d\right] \quad (1)$$

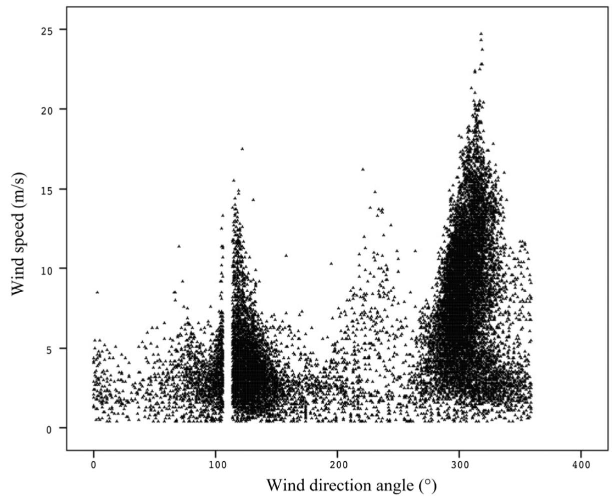

Fig. 1. Observed relation between wind speed and wind direction angle.

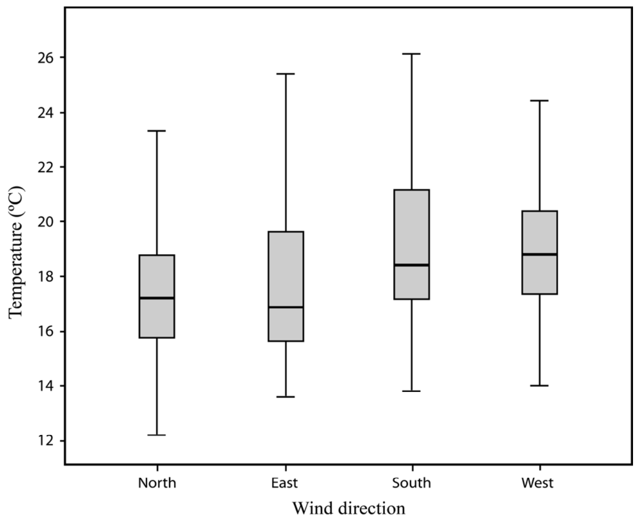

Fig. 2. Observed relation between temperature and wind direction.

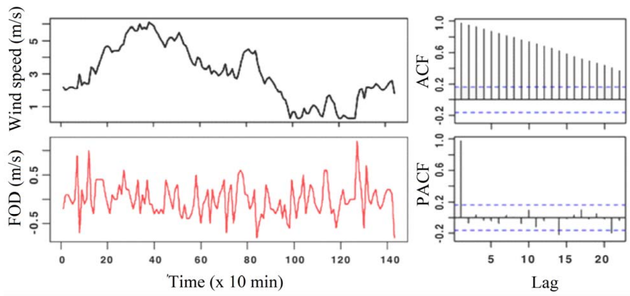

Fig. 3. Wind speed time series (top left), first order difference FOD (bottom left), autocorrelation ACF (top right) and partial autocorrelation PACF (bottom right).

D. ANN-based Forecasting Model

As already pointed out, the distinctive characteristic of the proposed approach for forecasting 24 h ahead of wind speed is the use of statistical feature parameters in the MLP model. To this end, typical feed-forward neural networks using the input vector defined in (1) are trained and tested. The neural networks employed for the purposes of this work consist of one hidden layer with p neurons, while the output layer is a vector of 24 components representing the estimated wind speed in the next 24 h (Fig. 4). Two different training methods are examined, namely the Levenberg-Marquardt algorithm (LMA) and the back-propagation algorithm (BPA). Before applying a training algorithm, the whole dataset is normalized in the interval [-1,1] using (2), where y_{min} equals -1, y_{max} equals 1, while x_{max} and x_{min} are the maximum and minimum values in the dataset.

$$y = y_{min} + (y_{max} - y_{\min})(x - x_{min}) / (x_{max} - x_{min}) \tag{2}$$

E. Prediction Error Indicators

Let us consider the time series $X_t = \{x_t \mid t = 1, 2, \ldots, k\}$ containing the real values captured by a sensor and $\hat{X}_t = \{\hat{x}_t \mid t = 1, 2, \ldots, k\}$ representing the forecasted values of X_t, where k is the length of the time interval. In the context of this work, three typical statistical error indicators are employed to evaluate the forecasting accuracy of the proposed model [31], namely mean absolute error (MAE), mean absolute percentage error (MAPE), and mean square error (MSE) defined in (3)-(5) respectively [32]. These measures, along with the coefficient of determination, are well-established evaluation criteria of model performance in the literature of wind speed/power forecasting [29], [33], [34]. Practically, MAE measures the average magnitude of errors between forecasted and observed data, MSE assesses the dispersion of error, while MAPE expresses accuracy as a percentage of the error.

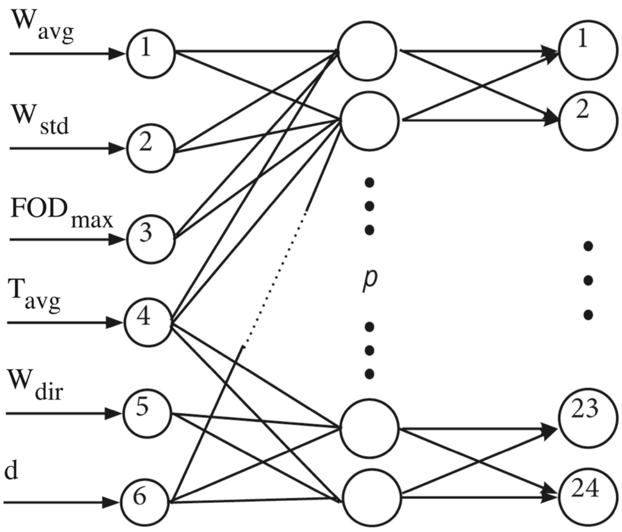

Fig. 4. Structure of the proposed ANN-based wind speed forecasting model.

$$MAE = \frac{1}{k}\sum_{t=1}^{k} \left| x_t - \hat{x}_t \right| \tag{3}$$

$$MAPE = \frac{1}{k}\sum_{t=1}^{k} \left| \frac{x_t - \hat{x}_t}{x_t} \right| 100\% \tag{4}$$

$$MSE = \frac{1}{k}\sum_{t=1}^{k} \left(x_t - \hat{x}_t \right)^2 \tag{5}$$

III. RESULTS

A. Training of ANN and Best MLP Architecture

The measurements of the model's parameters (collected for the time period from October 2010 to October 2011) were divided into a training dataset, which is used for calibrating the connection weights of the nodes in the MLP, and a testing dataset, which is used for assessing the performance of the model in forecasting after the connection weights of the nodes have been determined with the training process. Specifically, the training and testing datasets comprised 90% and 10% of the available data respectively. A cross-validation approach was adopted for monitoring the training process to avoid over-fitting, i.e. the training dataset was further partitioned into training and validation subsets to test the model during the training phase and stop the training process when the error in the validation subset increases.

The trial-and-error method was employed for determining a proper architecture for the MLP with one hidden layer. Table II presents the values of the prediction error indicators obtained for alternative MLP layouts, indicating that the one with p=13 neurons in the hidden layer provides a reasonable compromise between the size and performance of the ANN. Based on the 6x13x24 MLP structure, a second trial-and-error analysis was carried out to test four activation functions, namely log-sigmoid transfer function (logsig), linear transfer function (purelin), radial basis transfer function (radbas) and hyperbolic tangent sigmoid transfer function (tansig), using two training methods, namely LMA and BPA. Table III shows the values of the performance indicators of the model's output as well as the corresponding coefficients of determination R^2 in the training and testing datasets, for all the combinations of activation functions and training methods. Specifically, the training process of the ANNs revealed that LMA is faster than BPA and it achieves better fitting on the training set (Table III). For the LMA, the coefficient of determination R^2 ranges from 0.73 to 0.81 and for BPA from 0.71 to 0.78. The radial basis and tangent activation functions have the best fitting results when using LMA, with R^2 values equal to 0.80 and 0.81 respectively. Moreover, no results were obtained for the linear activation function using BPA. Regarding the computational requirements, it is noted that the execution times of the tests performed on a standard PC with Intel 1.6 GHz processor and 4 GB of RAM varied from 12 to 20 sec.

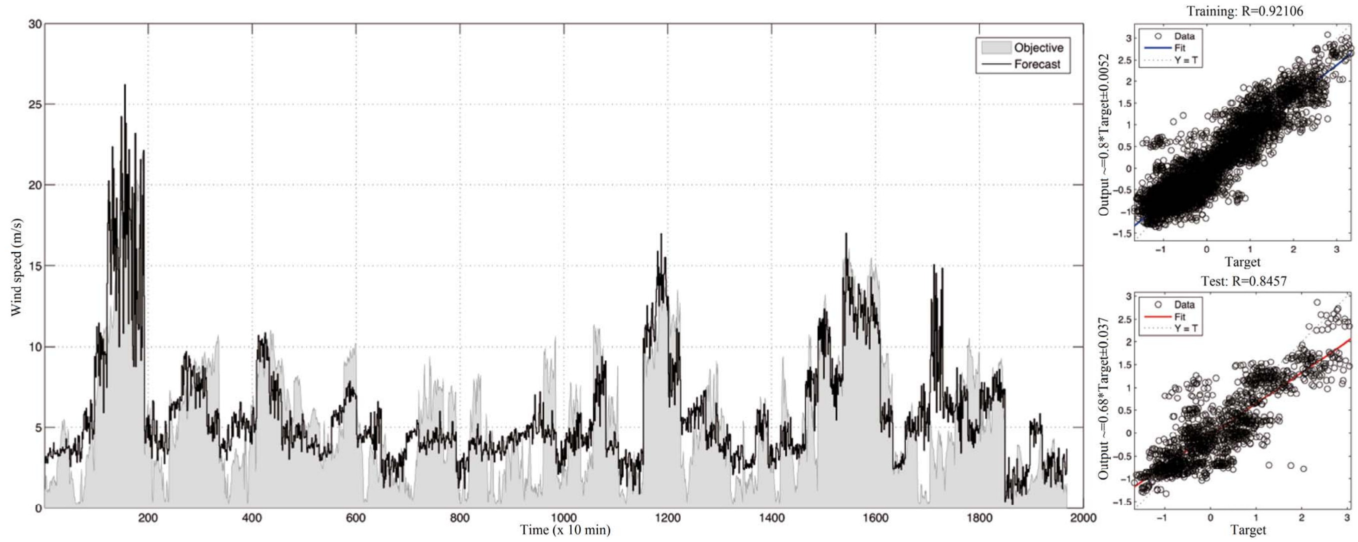

Fig. 5. Wind speed forecasting for 15 days (left) and correlation between actual and forecasted values for the training dataset (top right) and testing dataset (bottom right).

TABLE II. RESULTS OF TRIAL-AND-ERROR ANALYSIS FOR MLP ARCHITECTURE

MLP Layout	MAE (m/s)	MAPE (%)	MSE (m^2/s^2)
6x12x24	2.31	4.78	8.74
6x13x24	**2.31**	**4.62**	**8.54**
6x14x24	2.32	5.48	9.46
6x15x24	2.37	5.07	9.65
6x16x24	2.15	4.75	7.46
6x17x24	2.35	5.14	9.73

TABLE III. COMPARISON BETWEEN THE USE OF DIFFERENT ACTIVATION FUNCTIONS

Algorithm	Activation Function	MAE (m/s)	MSE (m^2/s^2)	R^2 training	R^2 testing
LMA	logsig	2.21	5.31	0.78	0.72
	purelin	1.98	5.62	0.73	0.81
	radbas	2.28	4.88	0.80	0.75
	tansig	**2.36**	**3.99**	**0.81**	**0.72**
BPA	logsig	1.95	4.87	0.78	0.70
	purelin	-	-	-	-
	radbas	2.21	5.04	0.77	0.73
	tansig	2.16	4.15	0.71	0.68

B. *Simulation for 15 Days*

Fig. 5 illustrates the output of the proposed ANN (training: LMA, activation function: tansig) for 15 days using a 24 h time frame, revealing a high correlation with the real measured values (correlation value close to 0.9) and thus a reasonable balance between forecasting accuracy and training computation requirements. In every new execution, the last 24 h of the actual wind data are included in the model to improve the quality of the results for the next 24 h forecast. Although all forecasts are represented in the same figure (Fig. 5), it is important to note at this point that the forecasting horizon is 24 h so that the results of the models are independent in each run and not related to the previous forecast.

IV. CONCLUSION

This paper presents a novel ANN-based wind speed forecasting model using statistical feature parameters of wind speed, wind direction and ambient temperature. A key characteristic of the proposed approach is the light-weight implementation, rendering it particularly suitable for mobile or embedded devices with low computational power, such as Arduino or Raspberry-Pi. More importantly, the comparison of the measured data with the output of the model shows that the proposed approach is capable of effectively representing the behavior of the wind speed for the 24 h ahead, and thus provides a fast algorithm that can be combined with wind turbine models in order to forecast their power output. Consequently, the proposed short-term wind speed forecasting model constitutes a practical solution that could be integrated as part of energy management systems for modern residences or small businesses, where the installed microRES include small-scale wind turbines, necessitating a reasonable balance between forecasting accuracy, availability of required data and computational requirements, while operating with a forecasting time horizon of 24 h.

References

[1] Z. Chen, J.M. Guerrero, and F. Blaabjerg, “A review of the state of the art of power electronics for wind turbines,” IEEE Trans. Power Electron., vol. 24, no. 8, pp. 1859-1875, August 2009.

[2] J.K. Kaldellis and D. Zafirakis, “The wind energy (r)evolution: A short review of a long history,” Renewable Energy, vol. 36, no. 7, pp. 1887-1901, July 2011.

[3] F. Yao, Z.Y. Dong, K. Meng, Z. Xu, H.H.-C. Iu, and K.P. Wong, “Quantum-inspired particle swarm optimization for power system operations considering wind power uncertainty and carbon tax in Australia,” IEEE Trans. Ind. Informat., vol. 8, no. 4, pp. 880-888, November 2012.

[4] Renewable Energy Policy Network for the 21st Century (REN21), Renewables 2013 Global Status Report. Paris: REN21 Secretariat, 2013.

[5] Global Wind Energy Council (GWEC), Global Wind Report Annual Market Update, 2012.

[6] N.A. Orlando, M. Liserre, R.A. Mastromauro, and A. Dell'Aquila, “A survey of control issues in pmsg-based small wind-turbine systems,” IEEE Trans. Ind. Informat., vol. 9, no. 3, pp. 1211-1221, August 2013.

[7] M. Bortolini, M. Gamberi, A. Graziani, R. Manzini, and F. Pilati, “Performance and viability analysis of small wind turbines in the European Union,” Renewable Energy, vol. 62, pp. 629-639, February 2014.

[8] S. Grijalva and M.U. Tariq, “Prosumer-based smart grid architecture enables a flat, sustainable electricity industry,” Innovative Smart Grid Technologies (ISGT), 2011 IEEE PES, pp. 1-6, January 2011.

[9] X. Ma, Y. Wang, and J. Qin, “Generic model of a community-based microgrid integrating wind turbines, photovoltaics and CHP generations,” Appl. Energy, vol. 112, pp. 1475-1482, December 2013.

[10] V.C. Güngör, D. Sahin, T. Kocak, S. Ergüt, C. Buccella, C. Cecati, and G.P. Hancke, “Smart grid technologies: Communication technologies and standards,” IEEE Trans. Ind. Informat., vol. 7, no. 4, pp. 529-539, November 2011.

[11] D.R. Carlson, H. Scott Matthews, and M. Bergés, “One size does not fit all: Averaged data on household electricity is inadequate for residential energy policy and decisions,” Energy Build., vol. 64, pp. 132-144, September 2013.

[12] K.N. Genikomsakis, C.S. Ioakimidis, H. Eliasstam, R. Weingraber, and D. Simic, “A non-myopic approach for a domotic battery management system,” in *Proc. 39th Annual Conf. IEEE Industrial Electronics Society (IECON 2013)*, Vienna, 2013, pp. 4522-4527.

[13] Y. Xu, Z. Y. Dong, Z. Xu, K. Meng, and K. P. Wong, “An intelligent dynamic security assessment framework for power systems with wind power,” IEEE Trans. Ind. Informat., vol. 8, no. 4, pp. 995-1003, November 2012.

[14] M. Lei, L. Shiyan, J. Chuanwen, L. Hongling, and Z. Yan, “A review on the forecasting of wind speed and generated power,” Renewable Sustainable Energy Rev., vol. 13, no. 4, pp. 915-920, May 2009.

[15] X. Zhu and M.G. Genton, “Short-Term Wind Speed Forecasting for Power System Operations,” Int. Stat. Rev., vol. 80, no. 1, pp. 2-23, April 2012.

[16] I. Colak, S. Sagiroglu, and M. Yesilbudak, “Data mining and wind power prediction: A literature review,” Renewable Energy, vol. 46, pp. 241-247, October 2012.

[17] B. Ernst, B. Oakleaf, M.L. Ahlstrom, M. Lange, C. Moehrlen, B. Lange, U. Focken, and K. Rohrig, “Predicting the wind,” IEEE Power Energy Mag., vol. 5, no. 6, pp. 78-89, November-December 2007.

[18] A. Togelou, G. Sideratos, and N.D. Hatziargyriou, “Wind power forecasting in the absence of historical data,” IEEE Trans. Sustain. Energy, vol. 3, no. 3, pp. 416-421, July 2012.

[19] K. Bhaskar and S.N. Singh, “AWNN-Assisted wind power forecasting using feed-forward neural network,” IEEE Trans. Sustain. Energy, vol. 3, no. 2, pp. 306-315, April 2012.

[20] T.H.M. El-Fouly, E.F. El-Saadany, and M.M.A. Salama, “One day ahead prediction of wind speed and direction,” IEEE Trans. Energy Convers., vol. 23, no. 1, pp. 191-201, March 2008.

[21] P. Louka, G. Galanis, N. Siebert, G. Kariniotakis, P. Katsafados, I. Pytharoulis, and G. Kallos, “Improvements in wind speed forecasts for wind power prediction purposes using Kalman filtering,” J. Wind Eng. Ind. Aerodyn., vol. 96, no. 12, pp. 2348-2362, December 2008.

[22] A. Shamshad, M.A. Bawadi, W.M.A. Wan Hussin, T.A. Majid, and S.A.M. Sanusi, “First and second order Markov chain models for synthetic generation of wind speed time series,” Energy, vol. 30, no. 5, pp. 693-708, April 2005.

[23] G. Li and J. Shi, “Applications of Bayesian methods in wind energy conversion systems,” Renewable Energy, vol. 43, pp. 1-8, July 2012.

[24] M.C. Alexiadis, P.S. Dokopoulos, and H.S. Sahsamanoglou, “Wind speed and power forecasting based on spatial correlation models,” IEEE Trans. Energy Convers., vol. 14, no. 3, pp. 836-842, September 1999.

[25] I.G. Damousis, M.C. Alexiadis, J.B. Theocharis, and P.S. Dokopoulos, “A fuzzy model for wind speed prediction and power generation in wind parks using spatial correlation,” IEEE Trans. Energy Convers., vol. 19, no. 2, pp. 352-361, June 2004.

[26] O. Kramer and F. Gieseke, “Short-term wind energy forecasting using support vector regression,” Adv. Intell. Soft Comp., vol. 87, pp. 271-280, 2011.

[27] J. Hu, J. Wang, and G. Zeng, “A hybrid forecasting approach applied to wind speed time series,” Renewable Energy, vol. 60, pp. 185-194, December 2013.

[28] D. Liu, D. Niu, H. Wang, and L. Fan, “Short-term wind speed forecasting using wavelet transform and support vector machines optimized by genetic algorithm,” Renewable Energy, vol. 62, pp. 592-597, February 2014.

[29] S.S. Soman, H. Zareipour, O. Malik, and P. Mandal, “A review of wind power and wind speed forecasting methods with different time horizons,” North American Power Symposium 2010, pp. 1-8, 2010.

[30] F. Wang, Z. Mi, S. Su, and H. Zhao, “Short-term solar irradiance forecasting model based on artificial neural network using statistical feature parameters,” Energies, vol. 5, no. 5, pp. 1355-1370, May 2012.

[31] C.S. Ioakimidis, S. Lopez, K.N. Genikomsakis, P. Rycerski, and D. Simic, “Solar production forecasting based on irradiance forecasting using artificial neural networks,” in *Proc. 39th Annual Conf. IEEE Industrial Electronics Society (IECON 2013)*, Vienna, 2013, pp. 8121-8126.

[32] J.G. De Gooijer and R.J. Hyndman, “25 years of time series forecasting,” Int. J. Forecasting, vol. 22, no. 3, pp. 443-473, 2006.

[33] A. Costa, A. Crespo, J. Navarro, G. Lizcano, H. Madsen, and E. Feitosa, “A review on the young history of the wind power short-term prediction,” Renewable Sustainable Energy Rev., vol. 12, no. 6, pp. 1725-1744, August 2008.

[34] X. Zhao, S. Wang, and T. Li, “Review of evaluation criteria and main methods of wind power forecasting,” Energy Procedia, vol. 12, pp. 761-769, September 2011.