

Article

## Harmonic Current Predictors for Wind Turbines

Jen-Hao Teng <sup>1,\*</sup>, Rong-Ceng Leou <sup>2</sup>, Chuo-Yean Chang <sup>2</sup> and Shun-Yu Chan <sup>2</sup>

<sup>1</sup> Departmental of Electrical Engineering, National Sun Yat-Sen University, Kaohsiung, Taiwan;

<sup>2</sup> Department of Electrical Engineering, Cheng-Shiu University, Kaohsiung, Taiwan

E-Mails: leou@csu.edu.tw (R.-C.L.); cychang@mail.csu.edu.tw (C.-Y.C.);

ingres@csu.edu.tw (S.-Y.C.)

\* Author to whom correspondence should be addressed; E-Mail: jhteng@ee.nsysu.edu.tw;

Tel.: +886-7-525-2000 (ext. 4118); Fax: +886-7-525-4199.

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**Abstract:** The harmonic impact caused by wind turbines should be carefully investigated before wind turbines are interconnected. However, the harmonic currents of wind turbines are not easily predicted due to the variations of wind speed. If the harmonic current outputs can be predicted accurately, the harmonic impact of wind turbines and wind farms for power grids can be analyzed efficiently. Therefore, this paper analyzes the harmonic current characteristics of wind turbines and investigates the feasibility of developing harmonic current predictors. Field measurement, data sorting, and analysis are conducted for wind turbines. Two harmonic current predictors are proposed based on the measured harmonic data. One is the Auto-Regressive and Moving Average (ARMA)-based harmonic current predictor, which can be used for real-time prediction. The other is the stochastic harmonic current predictor considering the probability density distributions of harmonic currents. It uses the measured harmonic data to establish the probability density distributions of harmonic currents at different wind speeds, and then uses them to implement a long-term harmonic current prediction. Test results use the measured data to validate the forecast ability of these two harmonic current predictors. The ARMA-based predictor obtains poor performance on some harmonic orders due to the stochastic characteristics of harmonic current caused by the variations of wind speed. Relatively, the prediction results of stochastic harmonic current predictor show that the harmonic currents of a wind turbine in long-term operation can be effectively analyzed by the established probability density distributions. Therefore, the proposed stochastic harmonic current predictor is helpful in

predicting and analyzing the possible harmonic problems during the operation of wind turbines and wind farms.

**Keywords:** wind turbine; harmonic current predictor; ARMA; probability density distribution

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## 1. Introduction

In the past few years, wind power generation has become the fastest growing renewable energy power generation technology in the World. Due to the mature techniques and commercialized bulk production, wind turbine cost has been reduced. In addition, severe commercial competition has resulted in rapidly decreasing costs in the past. At present, more than 40 countries in the World have wind turbines installed, mostly located in Europe, North America, and East Asia. Countries with large wind power generation are Denmark, Spain, Germany, U.S., *etc.* As more and more wind power generation systems have been connected to power systems, countries have begun to study regulations regarding interconnecting wind turbines and wind farms to power systems, and to analyze the resulting steady-state and dynamic impacts. Steady-state impact analysis includes voltage fluctuation, short-circuit current rush, power quality impact, and protection coordination. Dynamic impact analysis at least includes stability and voltage flicker [1–13].

The harmonic impact caused by wind turbines should be carefully investigated before the interconnection of wind turbines; especially, when wind power generation accounts for a certain percentage of the system power output. However, the harmonic currents of wind turbines are not easily predicted due to the variations of wind speed. If the harmonic current outputs can be predicted accurately, the harmonic impact of wind turbines and wind farms for power grids can be analyzed efficiently, therefore, this paper analyzes the harmonic current characteristics of wind turbines and investigates the feasibility of developing harmonic current predictors. In general, the harmonic current outputs of a power converter with constant power output can be formulated mathematically. However, when the power converter is used in wind turbines, its harmonic current outputs are difficult to formulate due the inertia of the blades and generator, especially when the wind speed changes instantaneously. The control algorithms and parameters used in the power converter of a commercialized wind turbine cannot be easily obtained also. Those factors make the harmonic current outputs stochastic and difficult to analyze. Therefore, how to use the measured harmonic data to develop harmonic current predictor to analyze the harmonic impact of the wind turbines and wind farms on power systems is an important issue [3,6–13]. Harmonic current prediction is difficult to some extent; thus, many previous studies have used neural networks for harmonic current prediction [14–16]. If the harmonic current characteristics can be known in advance, the harmonic current predictor for wind turbines can be realized effectively. Although some literature [11–13] has analyzed the harmonic current characteristic of wind turbines, this paper further analyzes these harmonic current characteristics at different wind speeds, and uses the measured data and harmonic current characteristic to propose harmonic current predictors.

Field measurements, data sorting, and analysis are conducted for wind turbines in this paper. Two harmonic current predictors are proposed based on the measured harmonic data. One is the harmonic current predictor implemented by the Auto-Regressive and Moving Average (ARMA) model, which

considers the change in wind speed and uses the measured harmonic data to calculate ARMA parameters. The ARMA model can then be used to predict the real-time harmonic current for the next time point. Although the prediction results of the ARMA-based harmonic current predictor can predict all orders of harmonic currents of wind turbine, the results aren't quite acceptable, especially for some harmonic orders. The presently measured wind turbine uses the power converter-based doubly fed inductor generator and is equipped with a harmonic filter, so the control results of this equipment will become very stochastic as the wind speed changes and consequently, the ARMA-based predictor has poor performance on some harmonic orders. This paper proposes another stochastic harmonic current predictor that considers the probability density distribution of harmonic currents. The measured harmonic data is then used to establish the probability density distribution for different orders of harmonic currents at different wind speeds. The proposed stochastic harmonic current predictor can then be implemented for long-term harmonic current prediction. The prediction results of the proposed stochastic harmonic current predictor show that the harmonic currents of a wind turbine in long-term operation can be effectively analyzed. Therefore, it will be helpful in predicting and analyzing the possible harmonic problems during the long-term operation of wind turbines and wind farms.

## 2. Field Measurements of Wind Turbine

This paper conducts long-term power quality measurements for a commercialized wind turbine of a doubly fed inductor generator type. The measured power quality parameters include three-phase voltages, currents, powers, harmonics, *etc.* The nameplate of the 1.5 MW rated power converter used for the wind turbine is illustrated in Figure 1.

The architecture and measurement point of the wind turbine are shown in Figure 2. The average power output of the wind turbine (kW) and average wind speed (m/s) per hour measured in a week are illustrated in Figure 3. There are occasionally higher wind speeds, but no corresponding outputs, as the wind turbine was shut down for some reasons at the time.

The wind turbine power output, the wind turbine rotation speed, and the wind speed are obtained from the power generation database of the wind turbine monitoring system, thus, the relationship between wind speed and power output can be established. Figure 4 shows the voltage harmonic and current harmonic spectra at a wind speed of 9.2 m/s. Other voltage harmonic and current harmonic spectra with respect to different wind speeds are also measured and recorded. The total number of measurements was 23,289. The field measurements can then be used to test and validate the proposed predictors.

**Figure 1.** Nameplate of power converter used in the wind turbine.



Figure 2. Architecture and measurement point of the wind turbine.

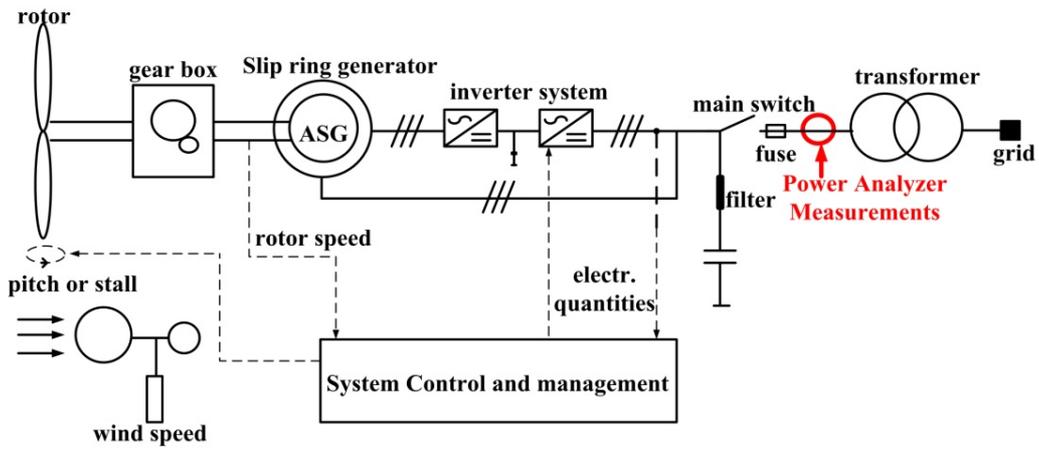


Figure 3. Average power output and wind speed per hour.

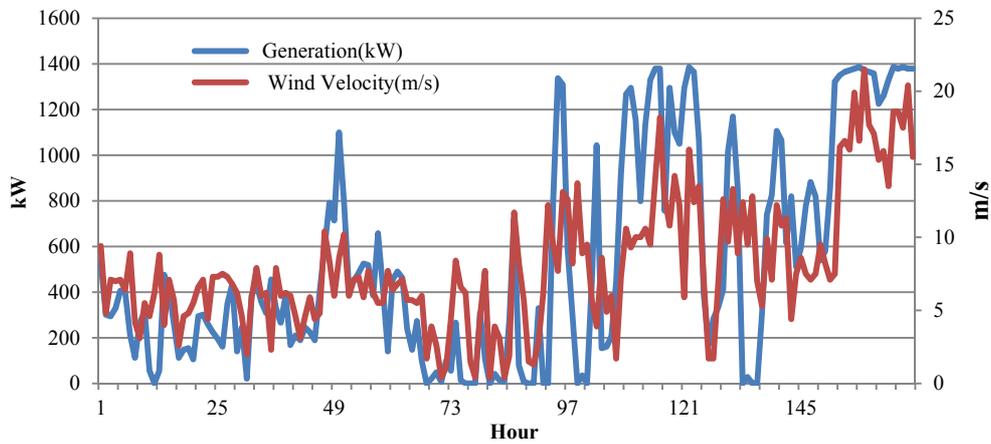
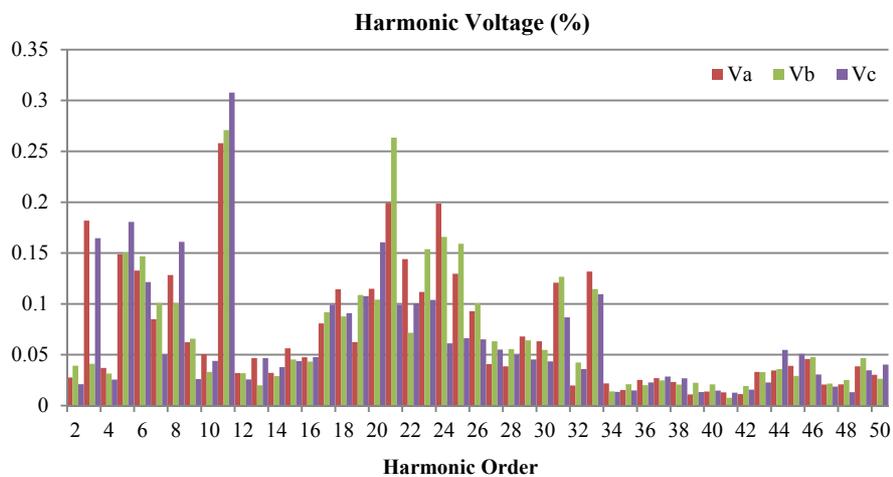
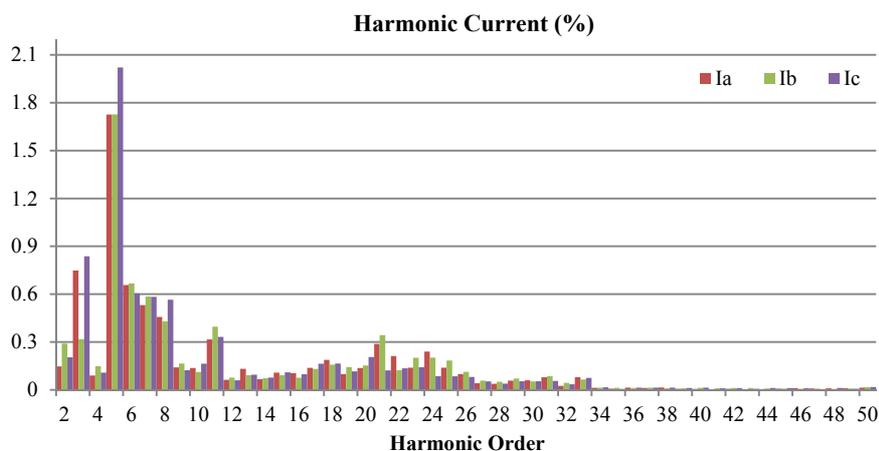


Figure 4. Voltage and current harmonic spectra at wind speed 9.2 m/s. (a) Voltage harmonic spectra; (b) Current harmonic spectra.



(a)

Figure 4. Cont.



(b)

### 3. Harmonic Current Predictor for Wind Turbines

This paper uses the measured harmonic data to design two harmonic current predictors. One is the real-time harmonic current predictor implemented by the ARMA model, which considers the change in wind speed. The other is the stochastic harmonic current predictor, which considers the output probability distribution of all orders of harmonic. The two harmonic current predictors proposed in this paper are described below.

#### 3.1. ARMA-Based Harmonic Current Predictor

The ARMA model contains Auto Regressive (AR) and Moving Average (MA). The p-order AR, AR(p), can be expressed as:

$$(z_t - \mu) - \varphi_1(z_{t-1} - \mu) - \dots - \varphi_p(z_{t-p} - \mu) = a_t \tag{1}$$

where  $z_t$  is the time series of the measured value;  $\mu$  is the mean value;  $\varphi_1, \varphi_2, \dots, \varphi_p$  are the parameters to be estimated, and  $a_t$  is the residual.

The q-order Moving Average (MA), MA(q), can be written as:

$$z_t - \mu = a_t - \theta_1 a_{t-1} - \dots - \theta_q a_{t-q} \tag{2}$$

where  $\theta_1, \theta_2, \dots, \theta_p$  are parameters to be estimated.

In certain cases, the simple AR model or MA model may require additional parameters to effectively establish the time series, the required parameters can be reduced by combining these two models. The ARMA(p,q) model is expressed as the following Equation (3):

$$(z_t - \mu) - \varphi_1(z_{t-1} - \mu) - \dots - \varphi_p(z_{t-p} - \mu) = -\theta_1 a_{t-1} - \dots - \theta_q a_{t-q} \tag{3}$$

The parameters for the ARMA model can be easily obtained by a computer program [17]; therefore, the parameters calculation procedure is not shown here. According to the basic formulas of ARMA as expressed in Equations (1–3), when the parameters in the ARMA model have been calculated for different harmonic orders using the measured data, the ARMA model can be used for real-time harmonic

current prediction. Using the  $h$ th order harmonic current as an example, the ARMA (2,3)-based harmonic current predictor can be expressed as:

$$I_{h,t}^{\text{pred}} - \mu_{h,t-1} = \phi_{h,t-1} (I_{h,t-1}^{\text{mea}} - \mu_{h,t-1}) + \phi_{h,t-2} (I_{h,t-2}^{\text{mea}} - \mu_{h,t-1}) - q_{h,t-1} a_{h,t-1} - q_{h,t-2} a_{h,t-2} - q_{h,t-3} a_{h,t-3} \tag{4}$$

$$\mu_{h,t-1} = \frac{\sum_{i=1}^{t-1} I_{h,i}^{\text{mea}}}{t-1} \tag{5}$$

$$a_{h,x} = I_{h,x}^{\text{mea}} - I_{h,x}^{\text{pred}} \quad x = t-1, t-2, t-3 \tag{6}$$

where  $I_{h,t}^{\text{pred}}$  is the predicted current for the  $h$ th order harmonic current at time period  $t$ .  $I_{h,t-1}^{\text{mea}}$ ,  $I_{h,t-2}^{\text{mea}}$  and  $I_{h,t-3}^{\text{mea}}$  are the measurements for the  $h$ th order harmonic current at time periods  $t-1$ ,  $t-2$  and  $t-3$ , respectively.  $\phi_{h,t-1}$ ,  $\phi_{h,t-2}$  and  $\theta_{h,t-1}$ ,  $\theta_{h,t-2}$ ,  $\theta_{h,t-3}$  are parameters for AR(2) and MA(3) for the  $h$ th order harmonic current, respectively.  $\mu_{h,t-1}$  calculated by Equation (5) is the mean value of the  $h$ th order harmonic current.  $a_{h,t-1}$ ,  $a_{h,t-2}$ ,  $a_{h,t-3}$  calculated by Equation (6) are the residuals for the  $h$ th order harmonic current at time periods  $t-1$ ,  $t-2$  and  $t-3$ .

### 3.2. Stochastic Harmonic Current Predictor Based on Probability Density Distributions of Harmonic Currents

The aforesaid ARMA model can be used to predict all harmonic outputs for the next time point. Most wind turbines at present use a power converter and are equipped with harmonic filters. Since the wind speed has large uncertainty and the control algorithms and parameters used in the power converter of commercialized wind turbine cannot be easily obtained, the harmonic current outputs of a wind turbine become highly stochastic and are difficult to predict especially when the wind speed change instantaneously. For example, Figure 2 shows the system architecture of the wind turbine measured in this paper. The wind turbine uses a power converter based doubly fed inductor generator and a harmonic filter is mounted at the output end. The control results of the wind turbine will become very stochastic as the wind speed changes. Therefore, the harmonic output must not be simply related to the harmonic output at previous time points. Even if there is a slight difference in the wind speed, harmonic output of wind turbine will be quite different. Figure 5 shows the 5/7/11th order harmonic currents of wind turbines when the wind speed ( $v_{ws}$ ) is 6.0–6.5 m/s.

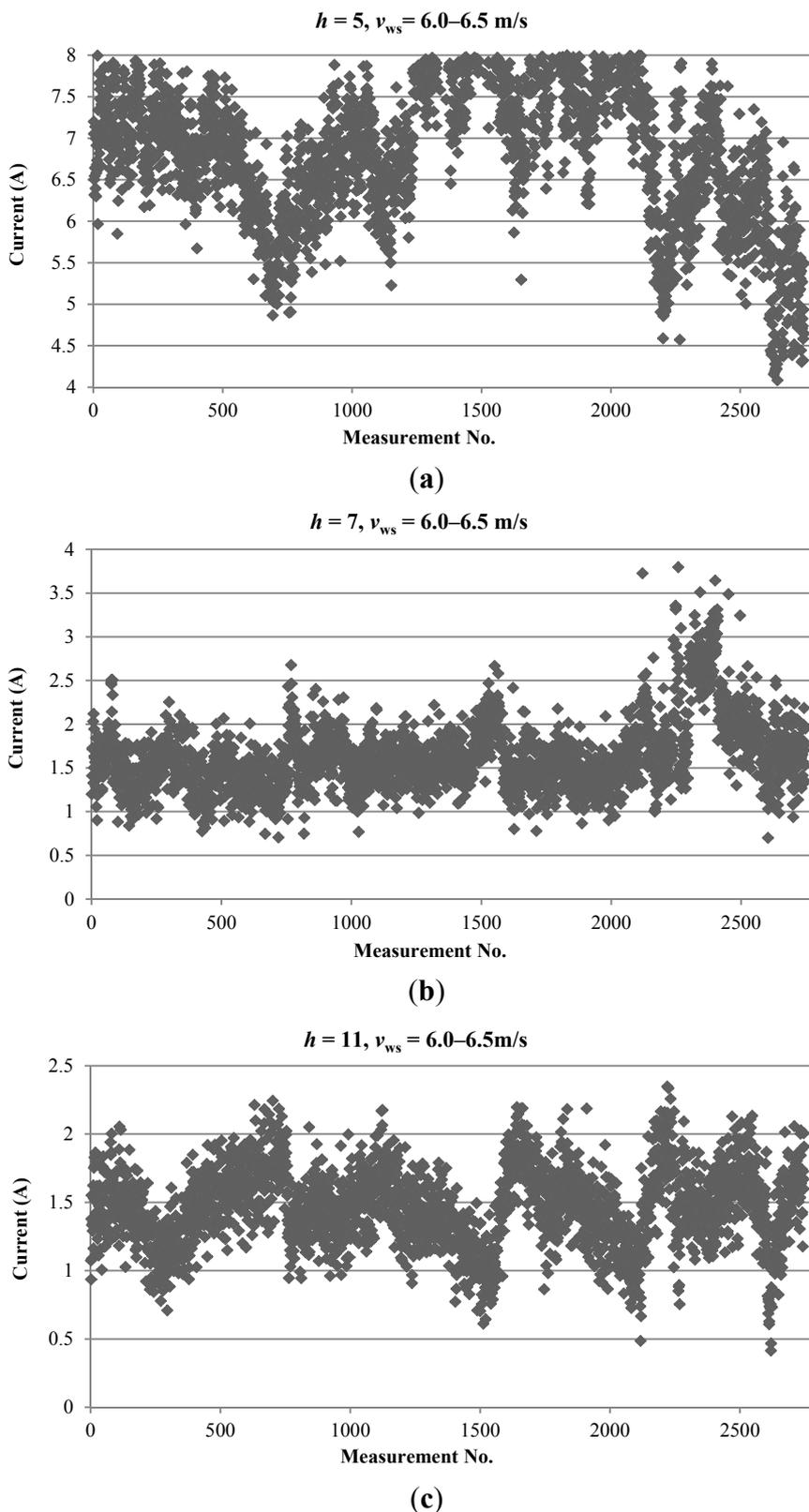
The  $x$ -axis in Figure 5 is the measurement no. and the  $y$ -axis is its corresponding harmonic current. It is observed that a slight difference in the wind speed would cause considerable changes in the harmonic current.

Although Figure 5 shows the harmonic currents of a wind turbine are very stochastic, if harmonic currents are segmented and the probability density distributions are calculated, then different viewpoints can be observed, as shown in Figure 6. It is seen that the probability density distribution is very close to normal distribution; therefore, Equations (7) and (8) are used to calculate the mean and standard:

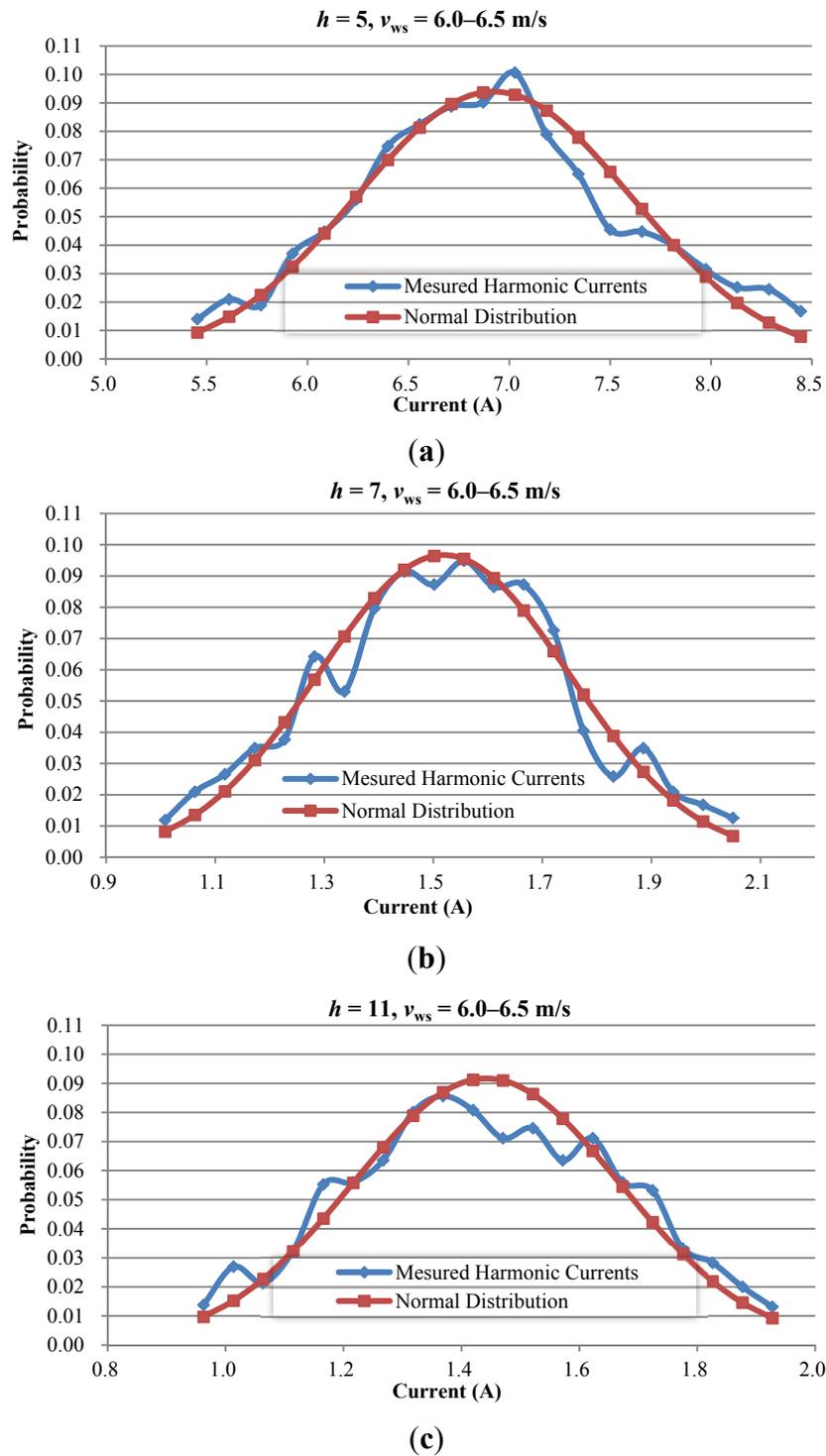
$$f_h^{\text{ws}} \left( I_h^{\text{ws}}; \mu_h^{\text{ws}}, (\sigma_h^{\text{ws}})^2 \right) = \frac{1}{\sigma_h^{\text{ws}} \sqrt{2\pi}} e^{-\frac{(I_h^{\text{ws}} - \mu_h^{\text{ws}})^2}{2(\sigma_h^{\text{ws}})^2}} \tag{7}$$

where  $f_h^{ws}(I_h^{ws}; \mu_h^{ws}, (\sigma_h^{ws})^2)$  is the probability density function of normal distribution for the  $h$ th order harmonic current established by  $\mu_h^{ws}$  and  $\sigma_h^{ws}$  of Equation (7) when the wind speed is within range  $v_{ws}$ .  $I_h^{ws}$  is the random variable for the  $h$ th order harmonic current when the wind speed is within range  $v_{ws}$ .

**Figure 5.** Output characteristics of the 5/7/11th order harmonic currents. (a) 5th order harmonic current; (b) 7th order harmonic current; (c) 11th order harmonic current.



**Figure 6.** Probability density distributions of the 5/7/11th order harmonic currents. (a) 5th order harmonic current; (b) 7th order harmonic current; (c) 11th order harmonic current.



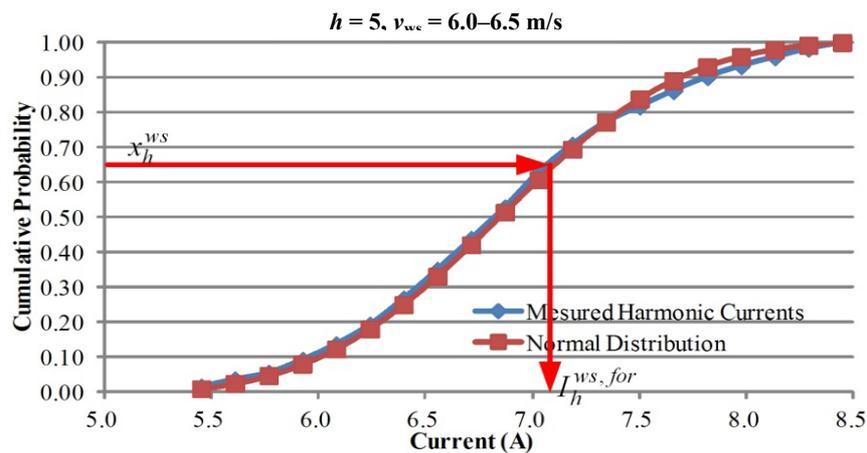
The cumulative distribution function of normal distribution can be established by Equation (9) and be expressed as:

$$F_h^{ws} \left( I_h^{ws}; \mu_h^{ws}, (\sigma_h^{ws})^2 \right) = \frac{1}{\sigma_h^{ws} \sqrt{2\pi}} \int_{-\infty}^{I_h^{ws}} e^{-\frac{(I_h^{ws} - \mu_h^{ws})^2}{2(\sigma_h^{ws})^2}} dI_h^{ws} \quad (8)$$

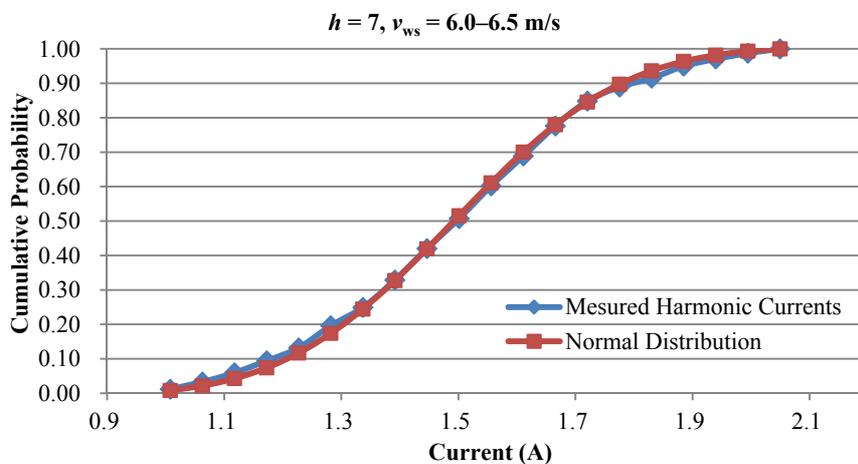
where  $F_h^{ws}(I_h^{ws}; \mu_h^{ws}, (\sigma_h^{ws})^2)$  is the cumulative distribution function of normal distribution of the  $h$ th order harmonic current when the wind is within range  $v_{ws}$ .

The cumulative distribution function, as Equation (10) established by actual measurement, can be used for harmonic current prediction. For example, when the wind speed range is 6.0–6.5 m/s, the measured cumulative distributions and cumulative distributions of normal distribution for the 5/7/11th order harmonic currents of wind turbine are illustrated in Figure 7. Once the cumulative distribution functions, as shown in Figure 7, are established, it can be used to transfer the value of cumulative probability to the harmonic current. A random variable with numerical value between 0 and 1 can be generated by a computer program randomly and used to simulate the value of cumulative probability. The harmonic current can then be obtained by inverting the value of cumulative probability from the cumulative distribution function. The concept is as shown in Figure 7a. In Figure 7a,  $x_h^{ws}$  is the generated random variable and  $I_h^{ws,for}$  is the predicted  $h$ th order harmonic current obtained by inverting  $x_h^{ws}$  from the cumulative distribution function.

**Figure 7.** Cumulative probabilities of the 5/7/11th order harmonic currents. (a) 5th order harmonic current; (b) 7th order harmonic current; (c) 11th order harmonic current.

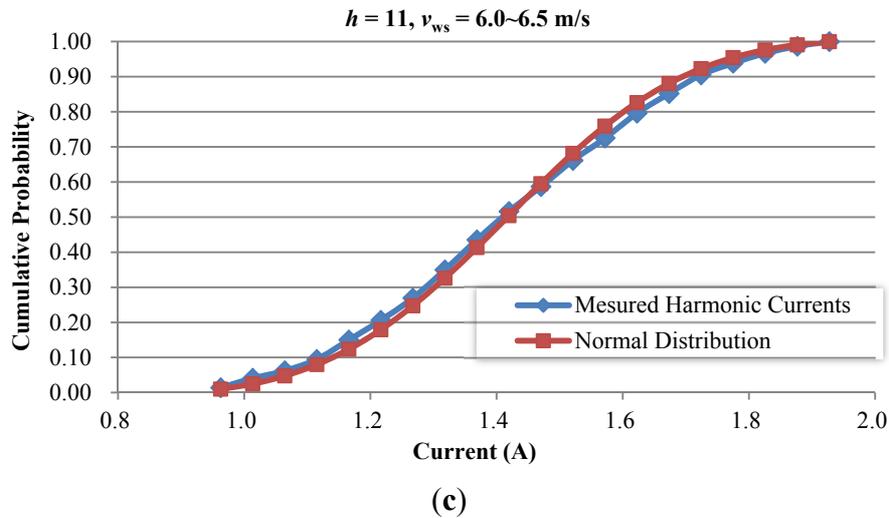


(a)



(b)

Figure 7. Cont.



#### 4. Test Results and Discussions

The proposed two harmonic current predictors are tested and their applicability is validated. Due to limited space, only the prediction results for the harmonic orders with larger harmonic currents such as the 5th, 7th and 11th harmonic orders are tested in this paper. However, the methods proposed in this paper can also be used to predict other harmonic orders *i.e.*, the 3rd order harmonic currents. The number of measured data points used in the following tests is 23,289.

##### 4.1. Prediction Results of ARMA-based Harmonic Current Predictor

This paper uses multiple ARMA models to build the prediction model for all orders of harmonic current. The 18,289 data of the measured 23,289 data are used to calculate various parameters in the ARMA model, and 5000 data are reserved to validate the prediction accuracy of ARMA model. The forecasted error of the model is calculated by Equation (11):

$$ER_{h,i} = \frac{|I_{h,i}^{mea} - I_{h,i}^{for}|}{I_{h,i}^{mea}} \times 100\% \tag{9}$$

where  $ER_{h,i}$  is the percentage error of the  $h$ th harmonic current of data number  $i$ .  $I_{h,i}^{mea}$  and  $I_{h,i}^{for}$  are the measured value and predicted value, respectively.

Table 1 uses 18,289 data points to build the ARMA models, and  $\phi_1$  and  $\theta_1$  are parameters of harmonic order 5, 7, 11, 13, 17, and 19. Due to limited space, the parameters for other ARMA models are not stated here. The harmonic prediction results of ARMA (1,1) and ARMA (2,3), implemented by the reserved 5000 data points are as shown in Tables 2 and 3. According to Tables 2 and 3, the ARMA (1,1) or ARMA (2,3) have only better prediction results for parts of harmonic orders; however, the whole forecasting errors are relatively large. As mentioned above, the measured wind turbine uses the power converter based doubly fed inductor generator and is equipped with a harmonic filter, the control results of these devices are highly stochastic as wind speed changes. Therefore, the ARMA model cannot accurately predict the harmonic output of wind turbine. That is to say, the harmonic currents of a wind

turbine cannot be predicted by a simple time series model. In addition, the harmonic currents at several time points must be used for the ARMA-based harmonic current predictor. Namely, the wind turbine must be equipped with a power quality analyzer to provide harmonic measurements to predict the harmonics at the next time point. Since most wind turbines have not been equipped with a power quality analyzer, the practicability of the ARMA model is further reduced.

**Table 1.** Parameters of ARMA (1,1) model.

Harmonic order	Parameters	
	$\phi_1$	$\theta_1$
5	0.99132	0.871431
7	0.994271	0.927426
11	0.997019	0.914273
13	0.993054	0.977224
17	0.993752	0.976071
19	0.988407	0.963316

**Table 2.** Prediction results of ARMA (1,1).

Harmonic Order	Error			
	Max.	Min.	Average	Standard deviation
5	82.62430	0.0007	7.4293	7.2188
7	332.3400	0.0027	15.0743	17.1146
11	259.0560	0.0041	13.9408	13.8874
13	336.1530	0.0056	35.5855	37.6699
17	495.9790	0.0057	31.0665	35.0412
19	2524.9900	0.0027	48.7375	85.6002

**Table 3.** Prediction results of ARMA (2,3).

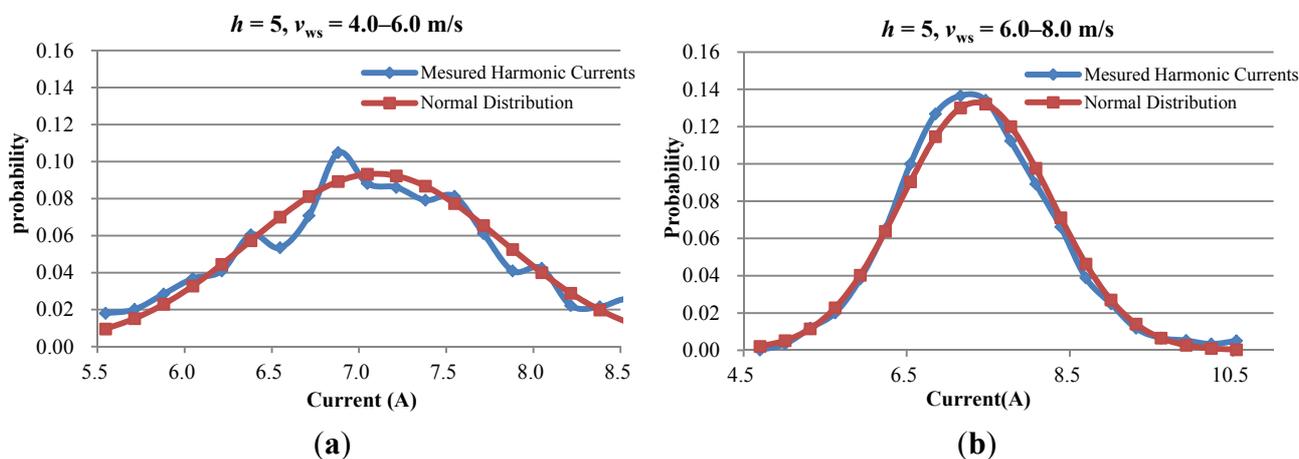
Harmonic Order	Error			
	Max.	Min.	Average	Standard deviation
5	77.7710	0.0042	7.4070	7.2547
7	328.0160	0.0070	15.1540	17.0847
11	256.9150	0.0062	13.9424	13.9027
13	333.1270	0.0133	35.5394	37.5889
17	491.7180	0.0032	30.9229	34.8254
19	2761.8000	0.0165	48.0389	81.9972

#### 4.2. Prediction Results of Stochastic Harmonic Current Predictor

In general, a smaller analyzed wind speed range requires more measurements for modeling. If more measurements are used, then a more accurate prediction can be anticipated. Since the modeling and validation of the stochastic harmonic current predictor both require more measurements; therefore, about a half of the measurements are used for model formation and the others are used for validation. In this paper, 55% of the measured data points in each wind speed range are used for model formation, and 45% are used for model validation. Besides, there are only 23,289 measured data, so the wind speed

ranges are therefore divided into 4–6 m/s, 6–8 m/s, 8–10 m/s, and above 10 m/s ranges. For simplicity, only the prediction results for the 4–6 m/s and 6–8 m/s wind speed ranges are discussed below. Figure 8 shows the probability density distribution of 5th harmonic current using 55% data for model formation, and the corresponding normal distribution for the different wind speed ranges. It is proved again by Figure 8 that the distributions of harmonic currents of wind turbine are very close to normal distribution. The mean and standard deviation corresponding to the normal distributions of all harmonic current orders in the wind speed ranges 4–6 m/s and 6–8 m/s are as shown in Table 4. Figures 9–11 show the forecasted probability density distributions of the 5/7/11th harmonic currents generated by the harmonic predictor and the 45% of measured data for validation. Figures 9–11 illustrate that the prediction results are very consistent with the measurement results for validation. Although the prediction results of stochastic harmonic current predictor are quite accurate, as compared with the prediction results of ARMA model in Tables 2 and 3, there remain some differences in prediction, as shown in Figures 9–11. The reason is the harmonic measurement data volume for establishing and validating probability distribution of all harmonics are slightly insufficient, thus, long-term measurement shall be conducted in the future and accuracy will be validated. This paper focused on the predictions of integer harmonics such as the 5th, 7th, 11th and 13th harmonic currents, since the inter-harmonic currents are not considered in most of the interconnection requirements. The inter-harmonic currents of wind turbine might cause some specified power quality problems for power grids; therefore, the extension of the proposed predictor for the low frequency inter-harmonic currents will be studied in the future.

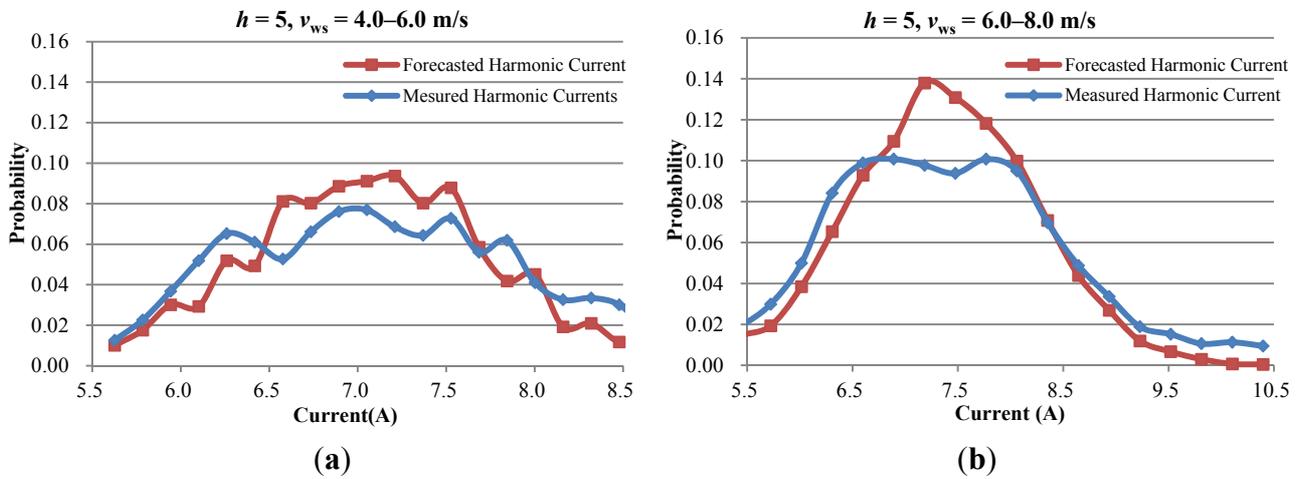
**Figure 8.** Probability density distributions of the 5th harmonic currents. (a) Wind speed range 4–6 m/s; (b) Wind speed range 6–8 m/s.



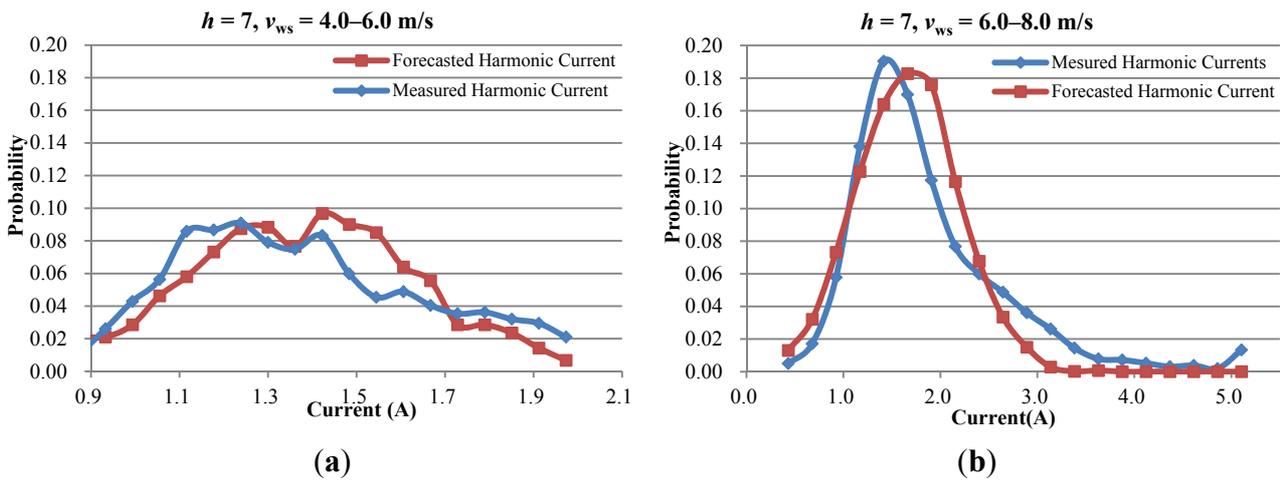
**Table 4.** Normal distribution parameters for the different order harmonic currents.

Harmonic order	Wind speed (4–6 m/s)		Wind speed (6–8 m/s)	
	Mean	Standard Deviation	Mean	Standard deviation
5	7.0997	0.7278	7.3567	0.9232
7	1.3728	0.2725	1.6626	0.5240
11	1.4312	0.2451	1.5279	0.2729
13	0.5777	0.1431	0.5532	0.1767
17	0.5014	0.1362	0.5850	0.2505
19	0.6556	0.1659	0.8099	0.3825

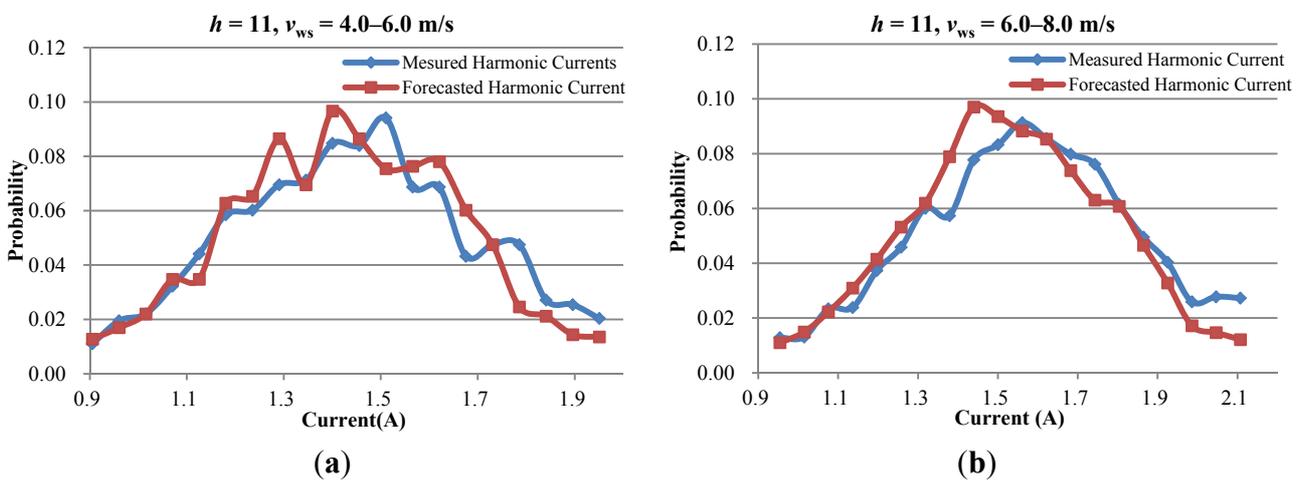
**Figure 9.** Measured and forecasted probability distributions of the 5th harmonic currents. (a) Wind speed range 4–6 m/s; (b) Wind speed range 6–8 m/s.



**Figure 10.** Measured and forecasted probability distributions of the 7th harmonic currents. (a) Wind speed range 4–6m/s; (b) Wind speed range 6–8m/s.



**Figure 11.** Measured and forecasted probability distributions of the 11th harmonic currents. (a) Wind speed range 4–6 m/s; (b) Wind speed range 6–8 m/s.



## 5. Conclusions

This paper conducted field measurements, data sorting, and analysis for the wind turbine, and uses the measured harmonic data to propose two harmonic current predictors. One was the real-time harmonic current predictor implemented by the ARMA model. The other was the stochastic harmonic current predictor considering the probability density distribution of harmonic currents. Test results of the ARMA-based harmonic current predictor showed that the prediction performances on some harmonic orders are poor. Relatively, the prediction results of stochastic harmonic current predictor showed that the harmonic currents of a wind turbine in long-term operation can be effectively analyzed by the established probability density distributions. Therefore, the proposed stochastic harmonic current predictor should have great potential to be used to analyze the harmonic impact caused by the grid-connected wind turbines and wind farms. Although test results demonstrated the performance of the proposed stochastic harmonic current predictor, other factors such as the effects of the grid supply conditions, magnetic loading of machine, the state of the DFIG drive itself, the harmonic filter installed in wind turbine *etc.* on the proposed harmonic current predictors should be further studied. Those topics will be investigated in the future research.

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