

## Adaptive decision fusion based framework for short-term wind speed and turbulence intensity forecasting: case study for North West of Turkey

Çiğdem DİNÇKAL<sup>1,\*</sup>, Behçet Uğur TÖREYİN<sup>2</sup>, Serhat KÜÇÜKALİ<sup>1</sup>

<sup>1</sup>Department of Civil Engineering, Faculty of Engineering, Çankaya University, Ankara, Turkey

<sup>2</sup>Informatics Institute, İstanbul Technical University, Turkey

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**Abstract:** In this paper, an online learning framework called adaptive decision fusion (ADF) is employed for short-term wind speed and turbulence intensity forecasting by use of wind speed data for each season for the city of İzmit, located in the northwest of Turkey. Fixed-weight (FW) linear combination is derived and used for comparison with ADF. Wind speeds and turbulence intensities are predicted from the existing wind speed data and computed turbulence intensities, respectively, using the ADF and FW methods. Simulations are carried out for each season and the results are tested on mean absolute percentage error criterion. It is shown that the proposed model captured the system dynamic behavior and made accurate predictions based on the seasonal wind speed characteristics of the site. The procedure described here can be used to estimate the local velocity and turbulence intensity in a wind power plant during a storm.

**Key words:** Wind speed, turbulence intensity, adaptive decision fusion, fixed weight linear combination, mean absolute percentage error

### 1. Introduction

The overall potential for wind energy depends heavily on accurately mapping and forecasting the wind resource (wind speed).

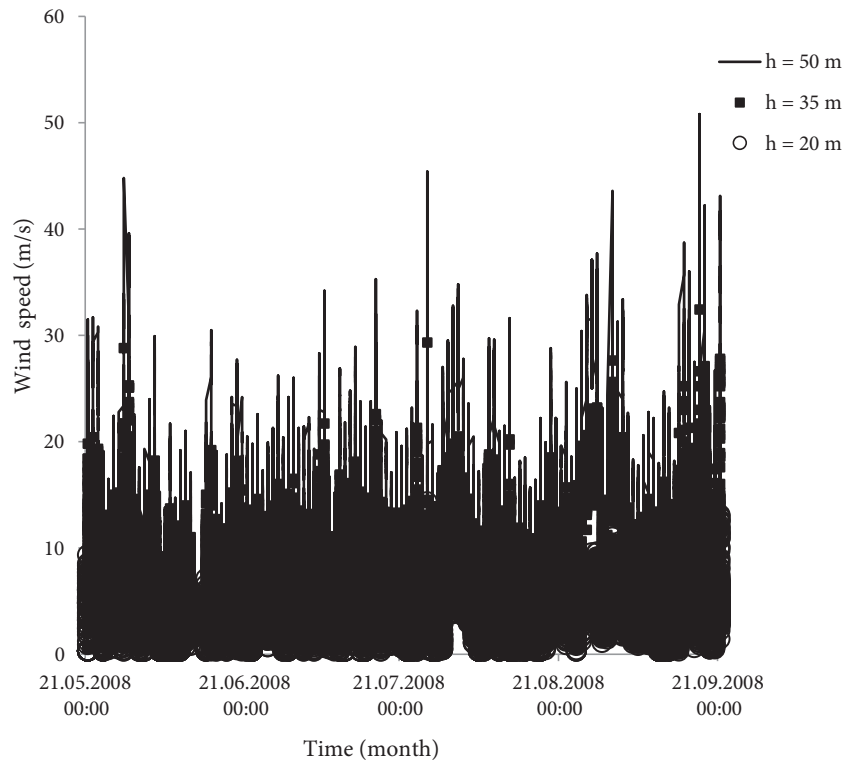
Power output of a wind turbine depends on wind speed, which varies with time, and depends on type of landscape and regional weather patterns.

The relationship of wind power and wind speed is explained best by the following formula:

$$P = \frac{1}{2} \rho A v^3, \quad (1)$$

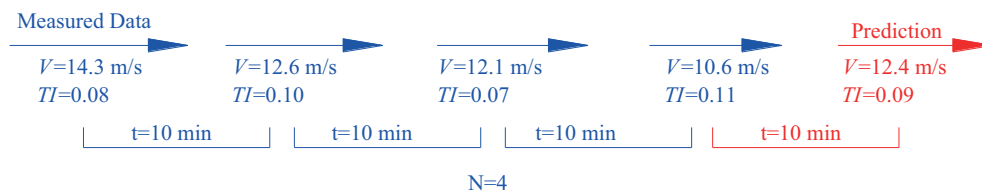
where  $\rho$  is the density of air and assumed to be  $1.225 \text{ kg/m}^3$ ,  $A$  is the swept area of the wind turbine, and  $v$  is wind speed [1,2]. Thus the only independent variable for calculation of wind power appears to be wind speed. As seen in Eq. (1), the relationship between wind speed and power is nonlinear, basically cubic. Any error in wind speed forecast will actually give a large (cubic) error in wind power. Hence, a small error in wind speed forecast can generate a larger error in wind power forecast. At first, the behavior of wind speed under different heights should be understood. For this reason, time series of wind speed were sampled every 10 min at different hub heights for 4 months (Figure 1).

\*Correspondence: [cdinckal@cankaya.edu.tr](mailto:cdinckal@cankaya.edu.tr)



**Figure 1.** Time series of wind speed at different hub heights for 4 months.

Wind speed forecast has been a very popular area of interest for many studies [3–9]. They have focused on wind speed forecasting for different regions using various methods, such as artificial neural networks, support vector machines, and adaptive Gaussian processes. In the literature, there are several methods for wind turbulence intensity estimations using different independent variables to estimate time-average turbulence characteristics for the given sampling duration. For instance, Kucukali and Dinçkal [2] estimated time-average turbulence intensity with the function of the relative submergence of the reference point. In addition, Satheesan and Kirkwood [10] estimated turbulence intensities from radar observations by using data clustering and fuzzy logic. On the other hand, Yanovsky et al. used the energy dissipation rate as an indicator of turbulence intensity and developed an algorithm to estimate energy dissipation rate based on the measured Doppler-polarimetric radar data [11,12]. Moreover, there are simulation programs, such as WindSim, that make turbulence estimations based on Richardson’s cascade energy equations and Reynolds number. However, the proposed method differs from the existing methods by forecasting the instantaneous turbulence intensity values from short-term time series of the measured turbulence intensity values without using any independent variables (Figure 2).

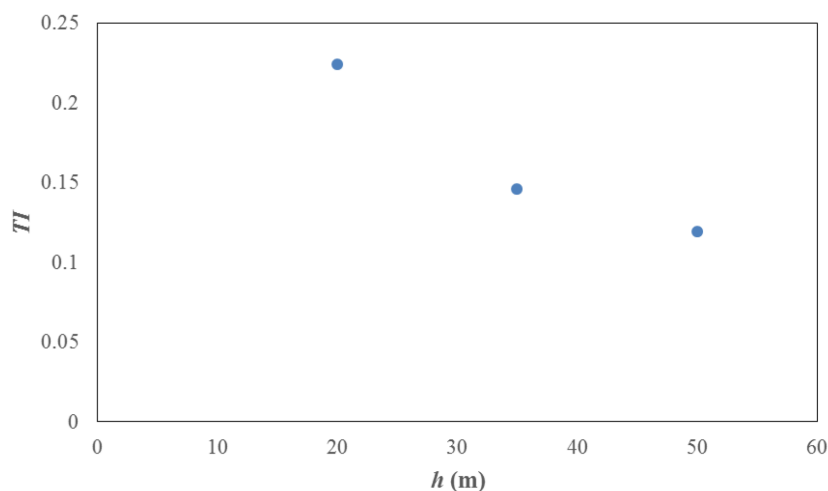


**Figure 2.** Definition sketch of the proposed methodology.

The turbulence analysis of a site is important because wind turbines are designed based on the wind speed and turbulence characteristics of the particular site. In addition, wind turbulence significantly influences the fatigue loads acting on wind turbines, and high levels of turbulence cause a reduction in energy output and speed up the fatigue of wind turbine mechanical parts [1]. Turbulence intensity is defined as the standard deviation of 10 min of measured wind speeds, as follows:

$$TI = \frac{\sigma}{V_{avg}} \quad (2)$$

where  $\sigma$  is the standard deviation of the wind speed and  $V_{avg}$  is the average of the wind speed for 10 min. As such, turbulence is directly proportional to deviation from the mean wind speed. A turbulence intensity value that is 0.10 or less is regarded as low-level turbulence, 0.10–0.25 is regarded as medium-level turbulence, and 0.25 or higher regarded as high-level turbulence [1,2]. In Figure 3, the variation in time-average turbulence intensity with height is presented.



**Figure 3.** Variation of time-average turbulence intensity with height from ground for the measured data.

As shown in Figure 3, at lower heights, turbulence intensity is higher. This is due to the fact that terrain influence on air flow decreases with height [2]. Those data indicate that wind turbines are subject to lower turbulence loads at higher levels.

The main aim of this work was to forecast not only wind speed but also, for the first time in the literature, turbulence intensity. For this reason, an online learning framework called adaptive decision fusion (ADF) is employed. A fixed-weight linear combination (FW) scheme is also used concurrently.

This method has been used successfully in different fields, such as image processing and wireless communications [13,14]. However, this online learning mechanism has not yet been applied to wind speed and turbulence intensity forecasting. This study shows the applicability of the proposed ADF for wind speed and turbulence intensity forecasting. It is also demonstrated that statistical learning based on past measurement values provides high performance forecasts compared to FW. The paper is organized as follows: measurement mast is defined, the ADF framework is described, and test results are provided.

## 2. Measurement mast

To determine the wind energy potential of İzmit (41.19°N, 30.30°E) in Turkey, a measurement mast 50 m in height was installed by 3E in the coastal region of İzmit. The measurement site is forest land consisting of a hill reaching a height of 120 m. Locations of the measurement mast and the nearby meteorological stations of Şile and Akçakoca are shown in Figure 4. The measurement mast is equipped with 6 anemometers (NRG #40 + Thies; Rock Hill, SC, USA) at 3 different levels (50, 35, and 20 m) and wind vanes at 48 m and 38 m. The anemometers were individually calibrated and calibration parameters were correctly introduced in the data logger. The wind data (average and standard deviation of wind speed and wind direction) were recorded at 10-min intervals. The uncertainty of the measured wind speed is  $\pm 0.2$  m/s. The measurement campaign covers the period from June 2008 to June 2009 [2]. Measuring sampling was done at 0.5 Hz and recorded every 10 min. The recorded data comprised mean, maximum, minimum, and standard deviation of wind speed and wind direction. Table 1 presents an overview of the instrument calibration in which the calibration factors of the wind measurement equipment is also given.



**Figure 4.** Locations of the measurement mast and the meteorological stations of Şile and Akçakoca.

**Table 1.** Calibration factors of the wind measurement equipment.

Instrument	Level [m]	Logger channel	Slope [m/s/Hz]	Offset [m/s]
Anemometer 1	50	1	0.762	0.27
Anemometer 2	35	2	0.761	0.28
Anemometer 3	20	3	0.760	0.29
Anemometer 4	50	4	0.0476	0.2632
Anemometer 5	35	5	0.0477	0.2678
Anemometer 6	20	6	0.0478	0.2730
Wind vane 1	48.5	7	-	-
Wind vane 2	18.5	8	-	-

### 3. Theoretical background and proposed methodology

#### 3.1. Adaptive decision fusion framework

Let  $\mathbf{v}(n) = [v(n-N), \dots, v(n-1)]^T$  be a vector of wind speed values  $v(i)$  of size  $N$ , and  $\mathbf{w}(n) = [w(n-N, n), \dots, w(n-1, n)]^T$  be the  $(n-N)$ th set of a weight vector consisting of weight values  $w(i, n)$ , where  $i = n-N, \dots, n-1$ . Initial weights,  $\mathbf{w}(0)$ , are set as  $N^{-1}$

The current wind speed,  $v(n)$ , is predicted as  $\hat{v}(n)$ , using a linear combination of  $N$  number of past values:

$$\hat{v}(n) = \mathbf{v}^T(n) \mathbf{w}(n) \quad (3)$$

Forecast error is computed by

$$e(n) = v(n) - \hat{v}(n) \quad (4)$$

The aim of the ADF framework is to minimize the forecast error. In order to do so, the weights are updated based on an approach using projection onto convex sets, as follows:

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu \frac{e(n)}{\|\mathbf{v}(n)\|^2} \mathbf{v}(n), \quad (5)$$

where  $0 < \mu < 2$  should be satisfied to guarantee the convergence [13,14].

A similar approach is utilized for turbulence intensity prediction.

Let  $\mathbf{TI}(n) = [TI(n-N), \dots, TI(n-1)]^T$  be a vector of turbulence intensity values  $TI(i)$  of size  $N$ , and  $\mathbf{w}'(n) = [w'(n-N, n), \dots, w'(n-1, n)]^T$  be the  $(n-N)$ th set of a weight vector consisting of weight values  $w'(in)$ , where  $i = n-N, \dots, n-1$ . Initial weights,  $\mathbf{w}'(0)$ , are set as  $N^{-1}$ .

The current turbulence intensity value  $TI(n)$  is predicted as  $\hat{TI}(n)$ , using a linear combination of  $N$  number of past values:

$$\hat{TI}(n) = \mathbf{TI}^T(n) \mathbf{w}'(n) \quad (6)$$

Turbulence intensity forecast error is computed by

$$e'(n) = TI(n) - \hat{TI}(n) \quad (7)$$

Similar to the speed prediction case, the weights used in turbulence intensity prediction are updated as follows:

$$\mathbf{w}'(n+1) = \mathbf{w}'(n) + \mu' \frac{e'(n)}{\|\mathbf{TI}(n)\|^2} \mathbf{TI}(n), \quad (8)$$

where  $0 < \mu' < 2$ .

#### 3.2. Fixed-weight linear combination method

For comparison purposes, a FW linear combination scheme was employed as well. In the FW case, the weights are kept at their initial values.

Providing several runs for ADF and FW, the mean absolute percentage error (MAPE) is computed by using the following formula:

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{v(i) - \hat{v}(i)}{v(i)} \right| \times 100 \quad (9)$$

A similar formula for turbulence intensity is used as follows:

$$MAPE' = \frac{1}{n} \sum_{i=1}^n \left| \frac{TI(i) - \hat{TI}(i)}{TI(i)} \right| \times 100 \quad (10)$$

The findings for each season and different values of  $N$  are summarized in the following tables for both wind speed and turbulence intensity, respectively.

As window size  $N$  increases, the correlation in wind speed values decrease. This yields a poorer wind speed forecast in both ADF and FW methods. However, in terms of  $MAPE$  condition, the best performance is achieved for  $N = 4$  using ADF. The  $MAPE$  results shown in Table 2 suggest that ADF performs better than a simple FW scheme as the changes in wind speed values are tracked and utilized to adjust weight values in an online manner. On the other hand, the predicted results for turbulence intensity are very close to each other for the ADF and FW methods, which are also presented in Table 3.

**Table 2.** MAPE values obtained by ADF and FW for wind speed forecast.

Methods:	N = 4		N = 10		N = 15	
	ADF	FW	ADF	FW	ADF	FW
Summer	11%	14%	11.5%	23%	13%	29%
Spring	11%	13%	14%	19%	15%	23%
Winter	11%	15%	13%	22%	14%	26%
Autumn	12%	15%	13%	23%	13%	28%

**Table 3.** MAPE' values obtained by ADF and FW for turbulence intensity forecast.

Methods:	N = 4		N = 10		N = 15	
	ADF	FW	ADF	FW	ADF	FW
Summer	4%	3.8%	4%	4.2%	3.8%	4.4%
Spring	3.8%	3.9%	3.7%	4%	3.7%	4.4%
Winter	3.6%	3.4%	3.6%	3.8%	3.5%	4%
Autumn	4%	3.8%	4%	4.3%	4.3%	4.5%

### 3.3. Experimental results

Measured data were gathered from İzmit to test the above methods [15].

The results are obtained for both wind speed and turbulence intensity.

### 3.4. Wind speed forecast

Anemometer readings recorded at a height of 50 m (Thies) were used to test the ADF method and compare it with FW. The monthly variation in the mean actual wind speed and predicted wind speed by ADF and FW methods is presented in Figure 5. Figures 6–13 show the comparison of correlations between actual wind speed and predicted wind speed by ADF and FW separately for each season. As seen in Figures 6–13, there exists a better correlation between actual wind speed values and predicted ones with ADF than with FW, especially in summer. While predicting wind speed, the superior performance of the ADF method is also apparent in the MAPE results for each season and  $N = 4$ , as shown in Figure 14.

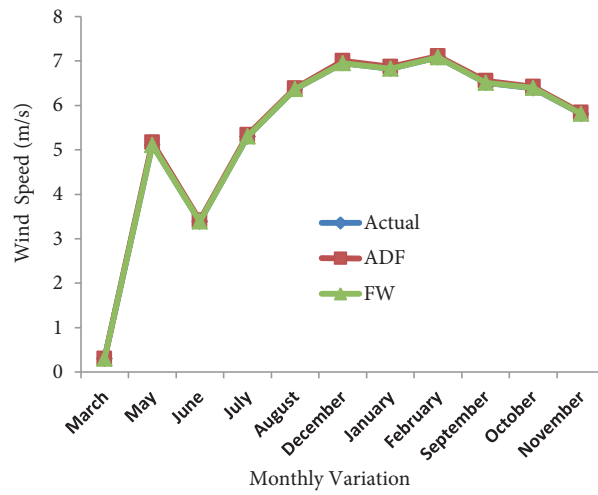


Figure 5. Monthly variation of the mean actual wind speed and wind speed predicted by ADF and FW methods.

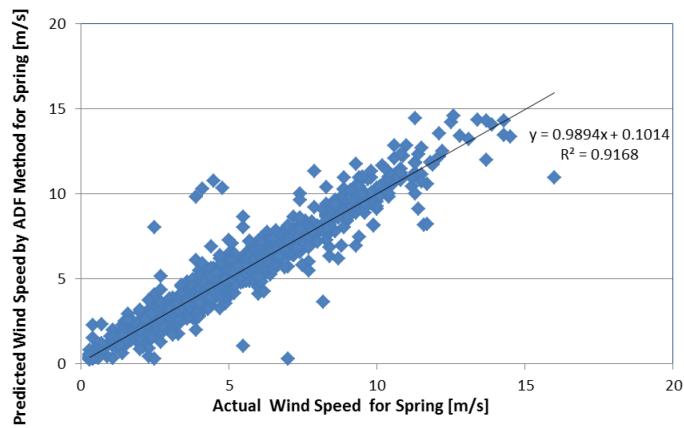


Figure 6. Correlation between actual wind speed and wind speed predicted by ADF and the regression line for spring.

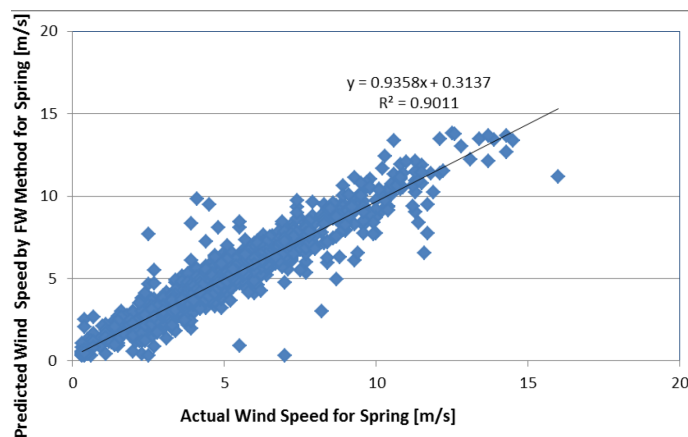


Figure 7. Correlation between actual wind speed and wind speed predicted by FW and the regression line for spring.

Figure 14 summarizes the error analysis for wind speed forecast. According to the results, the minimum error was achieved in spring with 11% by ADF and 13% by FW, only. In other words, spring is the best season

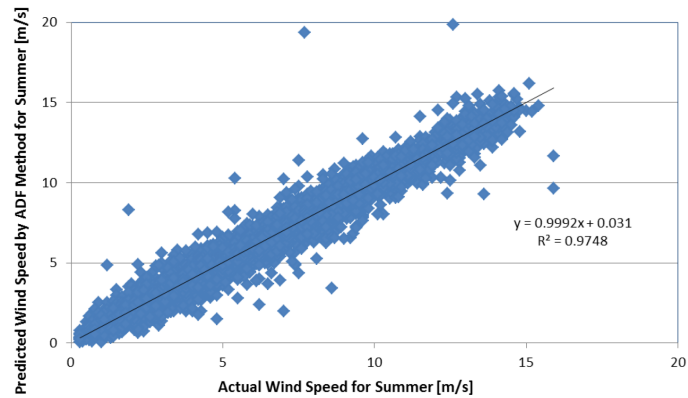


Figure 8. Correlation between actual wind speed and wind speed predicted by ADF and the regression line for summer.

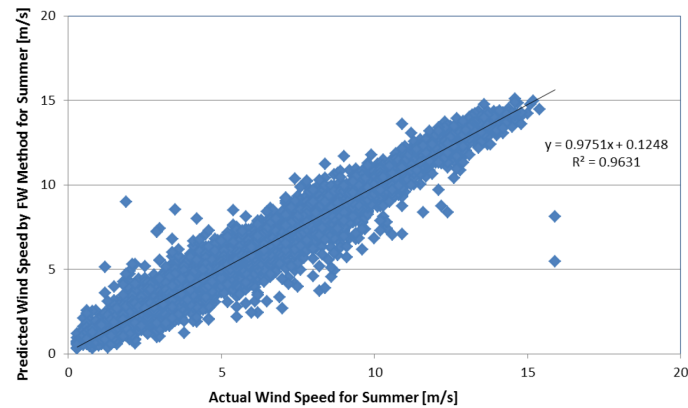


Figure 9. Correlation between actual wind speed and wind speed predicted by FW and the regression line for summer.

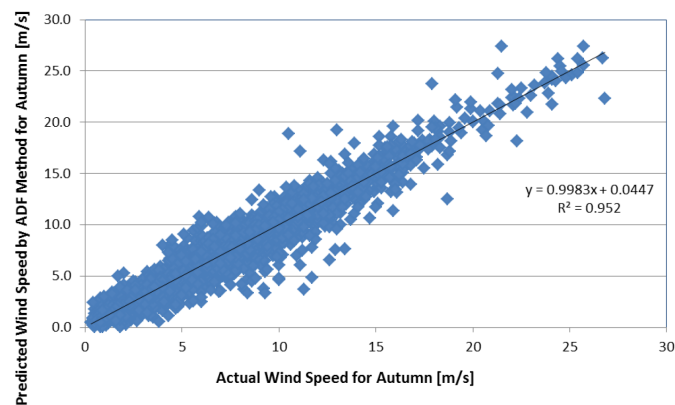


Figure 10. Correlation between actual wind speed and wind speed predicted by ADF and the regression line for autumn.

in which the actual wind speed almost matches up with the ones forecasted by both ADF and FW. Moreover, the error value for spring, 11%, is proof that forecasting by ADF, compared with the other methods used in the literature, is accurate [3,8]. Similar patterns can be seen in Figures 6–13, especially when there are sudden changes in wind speed values. The ADF method successfully keeps track of the rapid fluctuations in actual wind speed data. Those results indicate the better prediction performance compared to the FW method for all seasons.



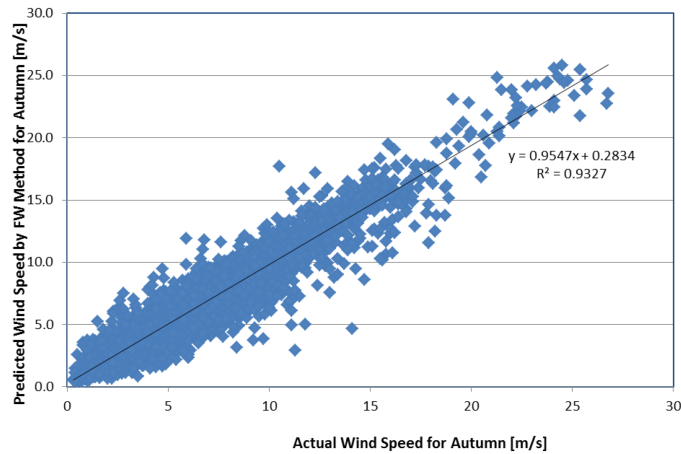


Figure 11. Correlation between actual wind speed and wind speed predicted by FW and the regression line for autumn.

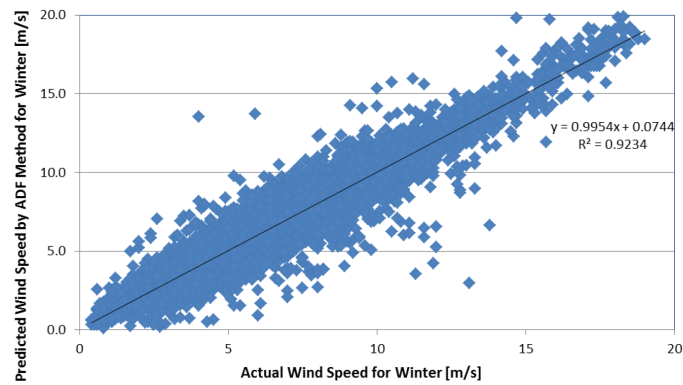


Figure 12. Correlation between actual wind speed and wind speed predicted by ADF and the regression line for winter.

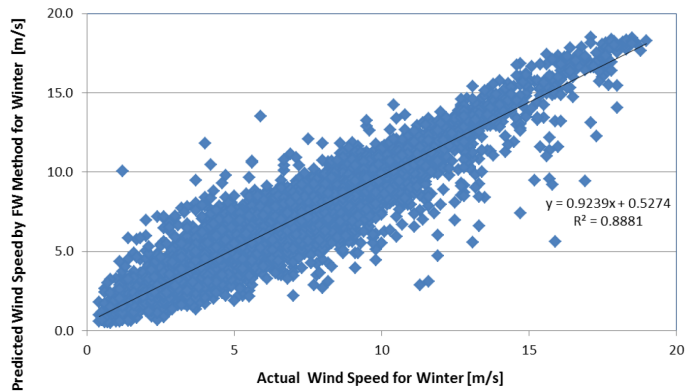
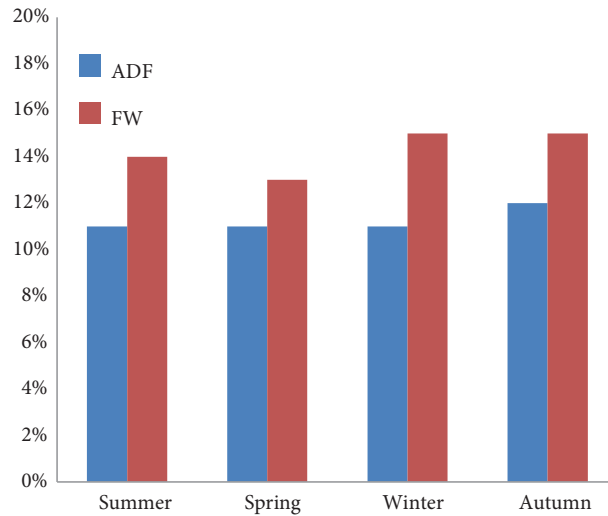


Figure 13. Correlation between actual wind speed and wind speed predicted by FW and the regression line for winter.

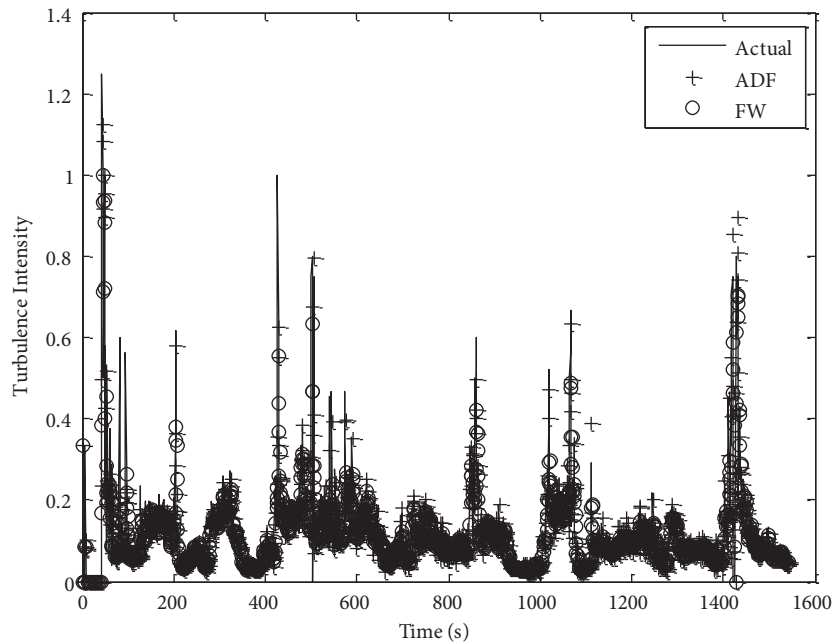
### 3.5. Turbulence intensity forecast

Figures 15–18 compare actual turbulence intensity and turbulence intensity predicted using the ADF and FW methods for each season. As shown in Figures 15–18, FW predicted rapid changes in turbulence intensity values slightly better than ADF. MAPE' results for each season and  $N = 4$  are also presented in Figure 19. Figure

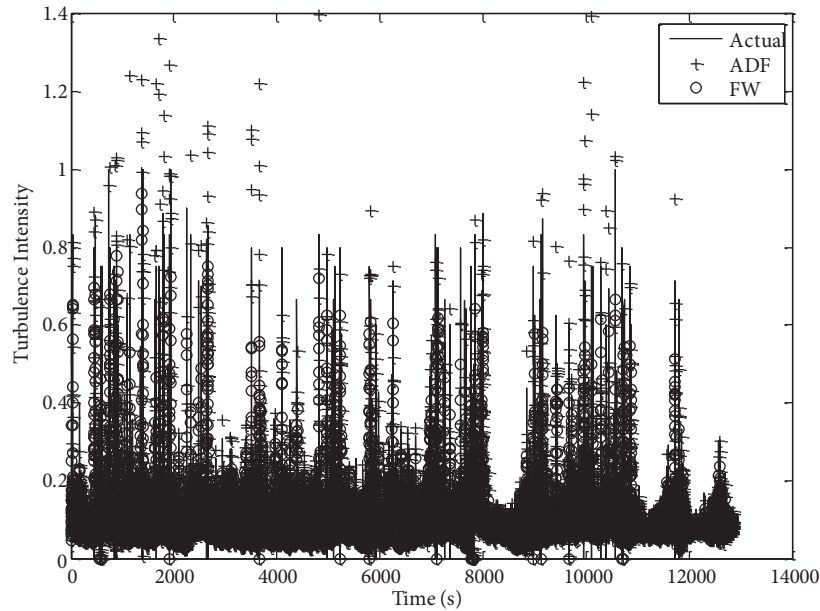


**Figure 14.** MAPE for wind speed predicted by ADF and FW.

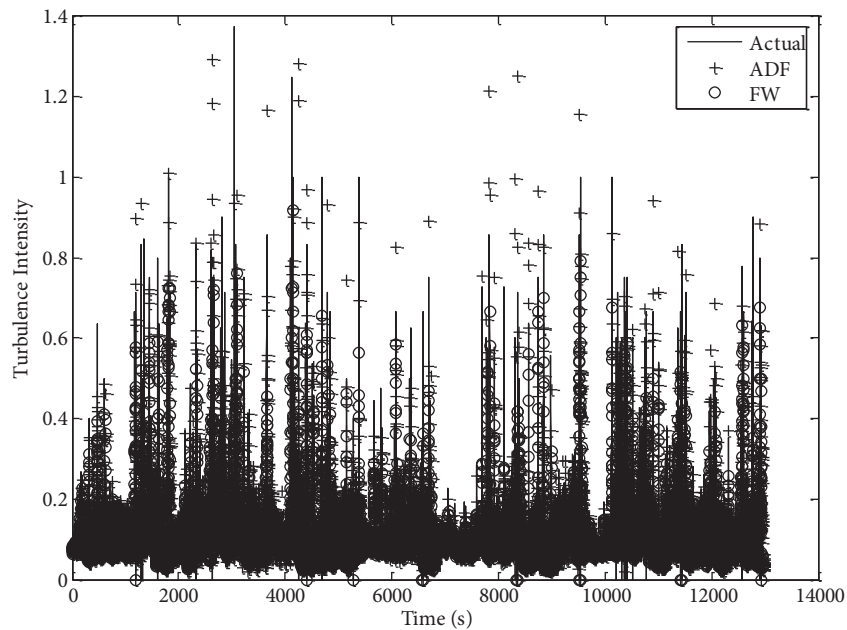
19 summarizes the error analysis for turbulence intensity. According to the results, the minimum error rate was achieved in winter, with a 3.6% error rate in ADF and 3.4% error rate in FW. In other words, winter is the best season in which the actual turbulence intensity value almost matched up with the ones forecasted by both ADF and FW. Furthermore, FW performed slightly better than ADF in the winter. It can be deduced that turbulence intensity prediction is a harder problem than wind speed prediction. Better online learning based methods should be devised to beat the baseline performance of the FW method.



**Figure 15.** Comparison of the actual turbulence intensity and turbulence intensity predicted by ADF and FW for spring.



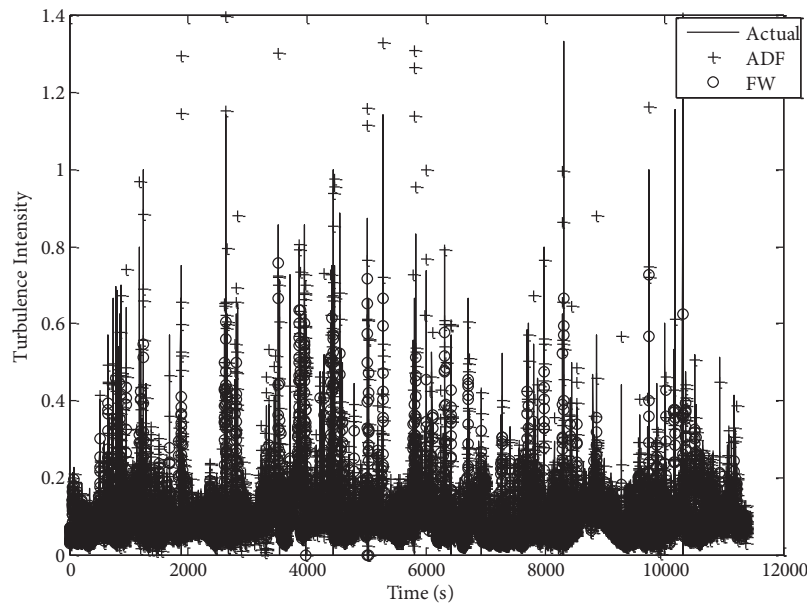
**Figure 16.** Comparison of the actual turbulence intensity and turbulence intensity predicted by ADF and FW for summer.



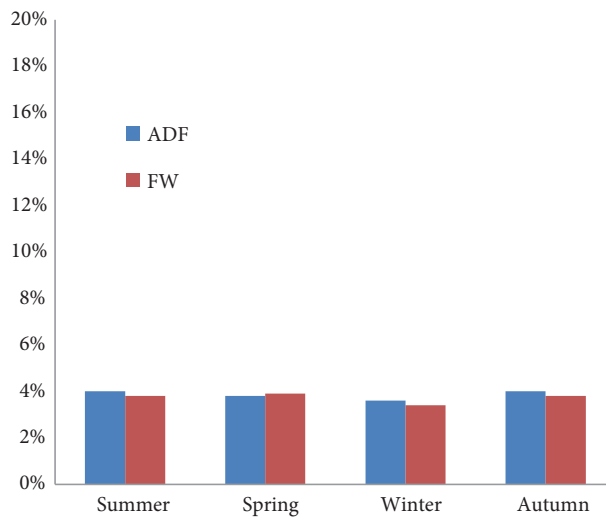
**Figure 17.** Comparison of the actual turbulence intensity and turbulence intensity predicted by ADF and FW for autumn.

#### 4. Concluding remarks

Wind speed and turbulence intensity are predicted by the developed ADF and FW methods. It is the first time in the literature that these methods are used in wind speed and turbulence intensity prediction. It should be noted that in the literature there are some studies [16,17] that made better predictions for wind speed data compared to the present study. In these studies, the numbers of test samples are two to three orders of



**Figure 18.** Comparison of the actual turbulence intensity and turbulence intensity predicted by ADF and FW for winter.



**Figure 19.** MAPE' for turbulence intensity by ADF and FW.

magnitude less than the number of samples used for the proposed ADF scheme. It should be noted that the performance of any prediction algorithm decreases as the number of samples increase. This is verified in Table 4, in which MAPE values corresponding to ADF and FW schemes for various numbers of samples are presented. It is evident that prediction performance degrades as sample size increases. Furthermore, the recent studies [16,17] lacked turbulence intensity estimations. The main advantage of the proposed methodology is that it can forecast wind speed and turbulence intensity simultaneously, which may have important implications for the performance and safety of wind turbines, especially during a storm. This study aimed to predict short-term future wind speed and turbulence intensity values from past records. The results of the present study suggest that one can predict the following wind speed and turbulence intensity values from antecedent measurements within acceptable relative error limits.

**Table 4.** The impact of the sample size on the prediction performance of the proposed methods.

Sample size	10	50	100	200	1000	10,000
ADF (%)	7.93	7.95	7.97	8.02	8.36	8.75
FW (%)	9.46	9.49	9.52	9.57	10.03	10.59

Consequently, the contribution of the paper is to introduce the ADF and FW methods in both wind speed and turbulence intensity forecasting. The main advantage of the ADF and FW methods is to forecast wind speed and turbulence intensity values in an online manner. In addition, the proposed methodology minimizes the prediction error while taking advantage of full physical modeling for both cases. Since velocity and turbulence intensity distributions strictly depend on site characteristics, the results of this study should be evaluated accordingly. The proposed methodology is a generic one and can be applied to other wind energy sites by following the procedure and adjusting relevant parameters. The advantage and merit of the proposed method can be summarized as follows: ease of use, replicability, modeling flexibility, and potential for integration with other techniques.

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