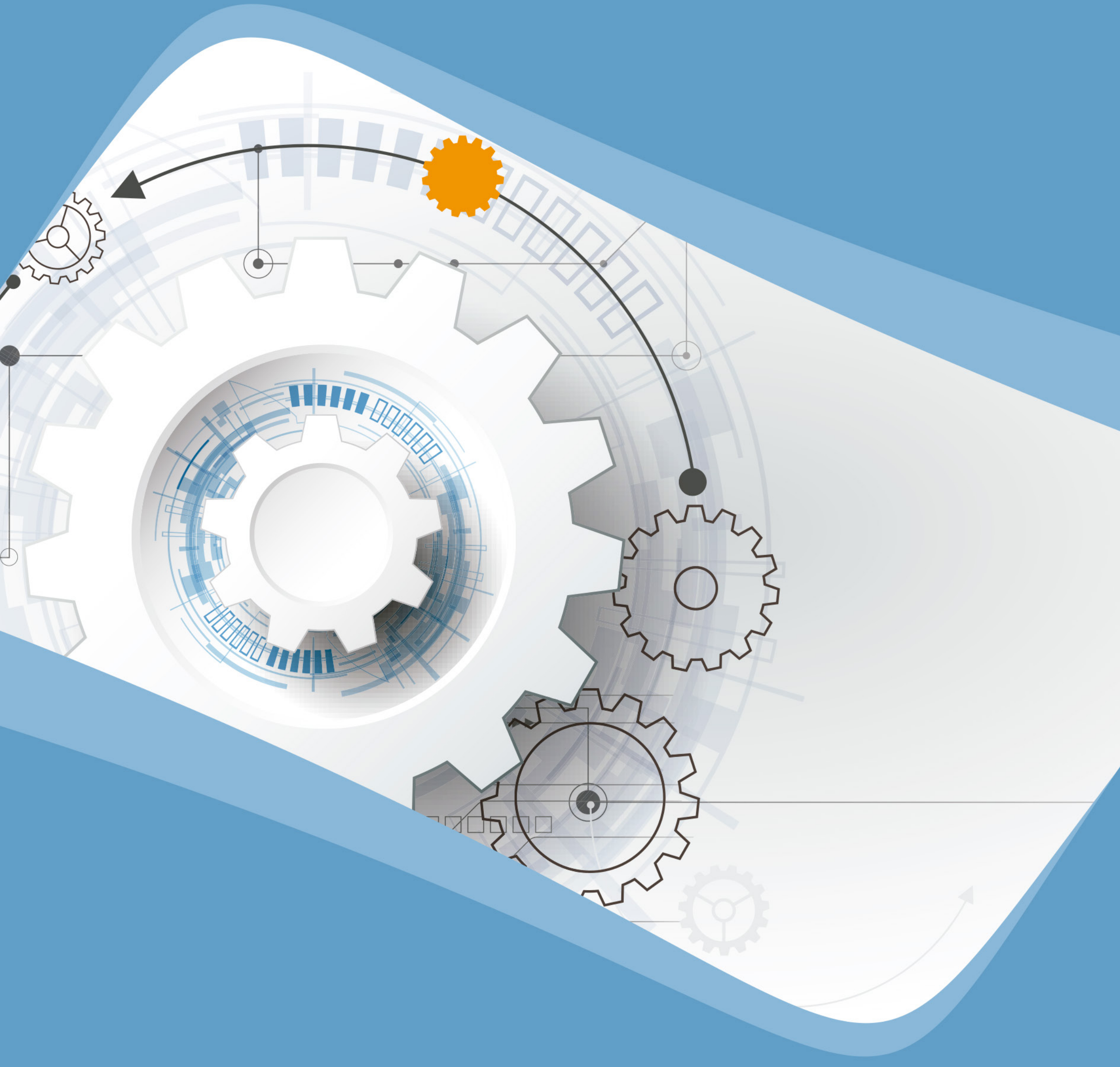
Resultados das Pesquisas e Inovações na Área das Engenharias 3



Henrique Ajuz Holzmann
(Organizador)

Atena Editora
Ano 2020

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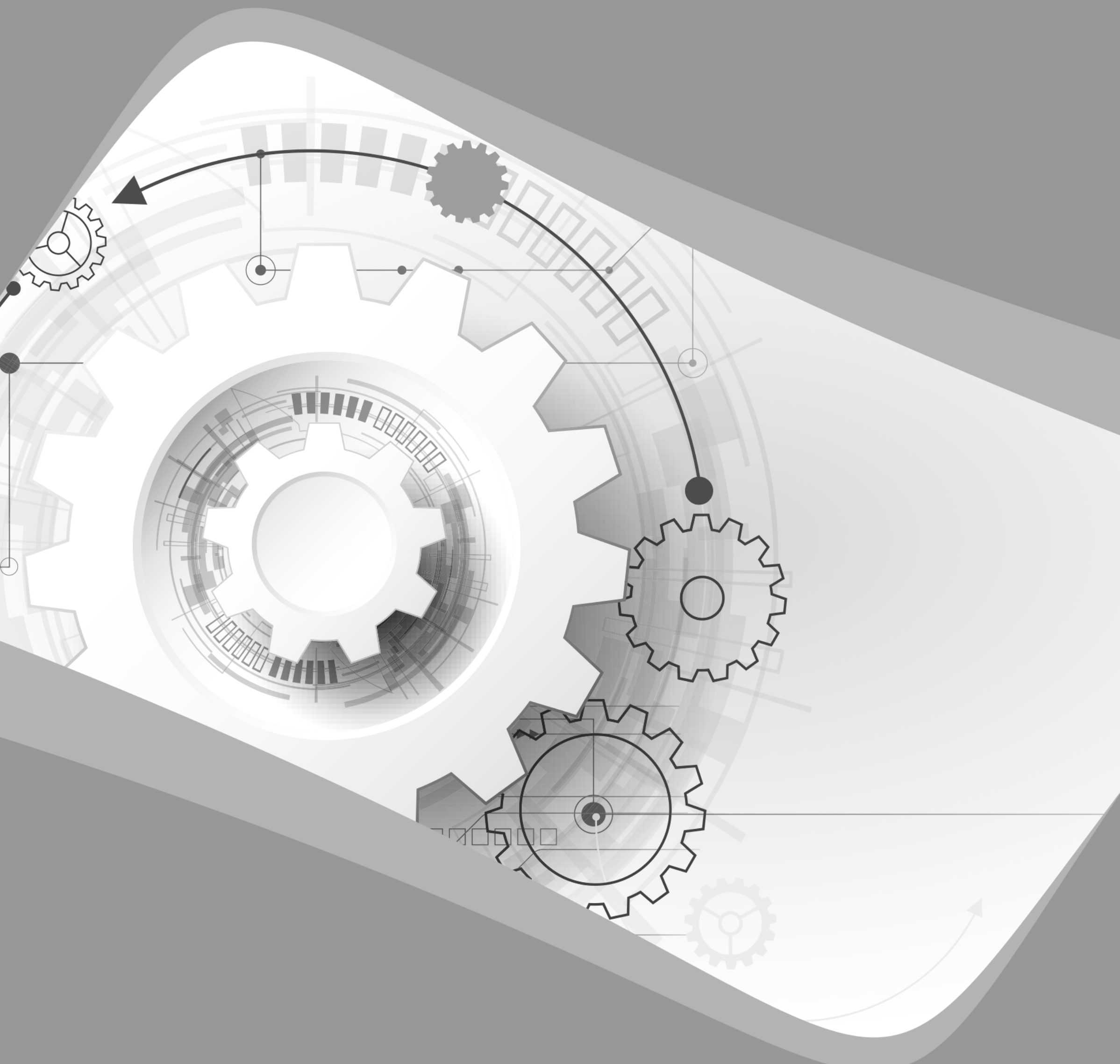

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APRESENTAÇÃO

Um dos grandes desafios enfrentados atualmente pelos engenheiros nos mais diversos ramos do conhecimento, é de saber ser multidisciplinar, aliando conceitos de diversas áreas. Hoje exige-se que os profissionais saibam transitar entres os conceitos e práticas, tendo um viés humano e técnico.

Neste sentido este livro traz capítulos ligados a teoria e prática em um caráter multidisciplinar, apresentando de maneira clara e lógica conceitos pertinentes aos profissionais das mais diversas áreas do saber.

Apresenta temas relacionados a área de engenharia mecânica e materiais, dando um viés onde se faz necessária a melhoria continua em processos, projetos e na gestão geral no setor fabril. Destaca os processos de reciclagem e sustentabilidade dentro do contexto empresarial e de resíduos gerados nos processos produtivos.

Da ênfase em alguns trabalhos voltados a prevenção de incêndios florestais através do emprego de técnicas especificas, além de realizar um levantamento econômico dos prejuízos gerados com os mesmos.

De abordagem objetiva, a obra se mostra de grande relevância para graduandos, alunos de pós-graduação, docentes e profissionais, apresentando temáticas e metodologias diversificadas, em situações reais.

Aos autores, agradeço pela confiança e espirito de parceria.

Boa leitura.

Henrique Ajuz Holzmann

SUMÁRIO

CAPÍTULO 10

ARIMA METHODOLOGY APPLIED TO DEVELOP A VERY SHORT-TERM WIND POWER FORECAST MODEL FOR THE PALMAS WIND FARM (BRAZIL)

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ABSTRACT: Wind power is already a consolidated power source for electricity generation, with more than 300 GW installed worldwide. It shows impressive growth numbers, such as an increase of 715% in the world installed capacity in the period of 2003 to 2013. In Brazil, the share of wind power on total energy production has increased from less than 1% to almost 5% in just five years. However, the electricity generated from the wind is a source of uncertainties for power system operators and can generate undesired variations in the energy quality for the energy system as a whole, decreasing its efficiency. To decrease the uncertainties and increase the efficiency of wind power generation are goals of wind power forecasting (WPF) models. This work shows the development of a probabilistic WPF model applied to the Palmas Wind Farm, located in the state of Paraná, Brazil. It was employed the well-known autoregressive integrated moving average (ARIMA) methodology to develop a very short-term WPF model. The performance of the model was evaluated using the mean absolute error (MAE) test, root mean squared error (RMSE) test and the Nash-Sutcliff (NS) index. It was found that the model is able to forecast up to three hours ahead, where the difference between the actual generated energy and the predicted energy reaches its maximum (8.47%). The quality of the forecasts, evaluated by the MAE, RMSE and Nash-Sutcliffe index also has shown satisfactory results. It is expected that the achievements of this work may be a reference for future works produced by the Department of Hydraulics and Sanitation (DHS) of the Federal University of Paraná.

KEYWORDS: Wind power, electricity generation, wind power forecast, probabilistic models, renewable energy.

METODOLOGIA ARIMA PARA PREVISÃO DA GERAÇÃO DE ENERGIA EÓLICA DE CURTÍSSIMO PRAZO APLICADA AO PARQUE EÓLICO DE PALMAS (PARANÁ, BR)

RESUMO: A energia eólica vem apresentando uma tendência de crescimento em sua capacidade instalada, tanto no Brasil quanto no mundo. O período entre 2003 e 2013 apresentou um crescimento de cerca de 715% na capacidade instalada mundial. No Brasil, a fatia de energia gerada pelo vento representa quase 5% do cenário energético atual, contra menos de 1% há cinco anos. A expansão da geração eólica

traz consigo desafios para o sistema elétrico e seus operadores, na forma de incertezas e variações sobre a qualidade da energia gerada. Diminuir essas incertezas e contribuir para tornar os sistemas eólicos mais eficientes são objetivos da previsão da geração de energia eólica (PGEE), foco deste trabalho. As previsões apresentadas resultam de um modelo probabilístico desenvolvido com base nas séries históricas de dados de velocidade de vento da Usina Eólio-Elétrica de Palmas (COPEL), localizada no estado do Paraná, Brasil. O modelo preditivo faz uso da metodologia de modelagem ARIMA (modelos auto-regressivos integrados e de médias móveis) para gerar os resultados exibidos ao longo do texto. O desempenho da PGEE desenvolvida mostrou-se satisfatória para um horizonte de até três horas, com um erro máximo inferior a 10%. Além de ser capaz de prever satisfatoriamente a geração da energia eólica, este modelo tem a pretensão de servir de referência para futuros trabalhos sobre o tema desenvolvidos pelo Departamento de Hidráulica e Saneamento da Universidade Federal do Paraná.
PALAVRAS-CHAVE: Energia eólica, geração de energia elétrica, previsão de geração eólica, modelos probabilísticos, energias renováveis.

1 | INTRODUCTION

In 2013 Brazil had 2.4 GW of installed wind power capacity. By March 2015, this amount had increased to 5.7 GW, and it was expected that the installed wind power capacity would reach 7.9 GW by the end of 2015 (Brasil, 2015). Data from the Brazilian Mines and Energy Ministry (MME) shows that, in July of 2015, wind power was responsible for 4.4% of the total energy produced in the country (Brasil, 2015). Five years earlier, wind power was responsible for 0.72% of the total power generation (Brasil, 2010). The increase in the amount of electricity produced by the wind in Brazil is aligned with the global trend of growth of wind power installed capacity. According to the Renewable Energy Policy Network for the 21st Century (REN 21), the global wind power installed capacity has reached 318 GW in 2013. In 2003 the world wind power installed capacity was only 39 GW. Thus, in ten years, the world wind power installed capacity has grown by 715% (REN21, 2013).

The increasing amount of wind power in the Brazilian and global energy markets was one of the main motivations for this research. The wind is an intermittent resource that cannot be controlled, making the power generation from the wind more challenging to manage when compared to traditional sources (Lu, 2008). On the other hand, wind power has advantages over other power generation sources as it is considered a clean energy source. Moreover, the installation of wind turbines is simpler when compared to the other power sources (except perhaps solar power) and it causes little environmental impact (Lu, 2008, Villela & Silveira, 2007).

In reality, wind power is a challenging matter for the operators of the electricity grid because the insertion of the wind power into the energy grid, if not done properly, can impact the quality of the distributed electricity. Distortions of the harmonics, voltage fluctuations and odd frequencies are examples of possible problems (Anaya-Lara et al., 2009). In this context, the wind power forecast (WPF) becomes an important tool to decrease the uncertainty associated with this type of power generation and different types of WPF can be developed, with varied forecast horizons and approaches. Very short-term and short-term forecasts usually are built on statistical methods and rely mainly on the wind speed and wind direction time series. On the other hand, mid-term and long-term forecasts employ numerical weather forecast methods to develop the WPF model (Monteiro et al., 2009). Regardless of the choice of the forecast horizon, the models are used to estimate the future wind power generation, a piece of information that can facilitate the insertion of the electricity into the power grid by the system operators (Monteiro et al., 2009, Wang et al., 2009). The WPF can also be employed as a tool for planning the maintenance schedule for the wind farms. For all these reasons, WPF can be considered as a fundamental tool for the power sector (Monteiro et al., 2009).

This work presents the development of a statistical WPF model built on top of the past wind speed time series from the Palmas Wind Farm, located in the state of Paraná, Brazil. The model uses auto-regressive and moving average models (ARIMA models) to forecast wind speed and wind power at the Palmas site. The chosen methodology has been widely employed for forecasting purposes and can serve as a baseline model, and its results can later be compared to the ones generated by more complex models, such as models based that use artificial intelligence algorithms (e.g., support vector regression or artificial neural networks (Rodrigues et al., 2015).

The developed model provided reliable forecast results up to three hours ahead, where it showed an MAE (Mean Absolute Error) of 0.99 m/s during summertime and 1.19 m/s during wintertime. The Nash-Sutcliffe (NS) index showed positive results for the three hours ahead forecast, about 0.57, for both seasons. The difference between real and forecasted data for the selected period of assessment was less than 10%, as illustrated in Figure 7.

The development of a reliable WPF was the main goal of this work, which was conceived to be a baseline study, a reference for future studies developed by the team of the Department of Hydraulics and Sanitation (DHS) of the Federal University of Paraná. The secondary goal of this work is perhaps to promote this field of study within the department.

This paper is organized as follows: section 2 exhibits the details of the Palmas Wind Farm; section 3 presents the methodology behind the forecast model; section 4 presents and discusses the results; finally, section 5 shows the conclusions.

2 I THE PALMAS WIND FARM

The models developed in this work were calibrated and validated based on the wind speed data retrieved from the Palmas Wind Farm, located in the State of Paraná, Brazil (26° 34’46,8 S e 51° 41’51,0 W). The site has a plain relief with few and smooth hills and is located 1350 m above sea level.

The main economic activity of the region is cattle raising, and the fields of Palmas are used for pasture, and the installation of the wind farm exerted little impact on the economic activity of the region (Camargo, 2005).

The wind farm consisted of five Enercon model E-40 wind turbines, described in Table 1 below.

Hub height (m)	44.0
Rotor diameter (m)	40.3
Cut-in wind speed (m/s)	2.5
Rated wind speed (m/s)	12.0
Cut-out wind speed (m/s)	25.0

Table 1 - Enercon E-40 Wind Turbine Specifications

The Palmas Wind Farm was the first of its kind installed in the Southern part of Brazil, and its construction took just a week. The wind farm began generating electricity in February of 1999 (Copel, 2013).

3 I METHODOLOGY

The essential data for this work was made available by COPEL - Companhia Paranaense de Energia (Paraná Power Company). The database used in this work consisted of ten-minute wind speed and wind power data series, ranging from January 2008 to December 2011. The wind speed data was retrieved from an anemometer installed at the wind farm, while the wind power data series were acquired from the SCADA system. The years of 2008-2010 were used to develop the model, and the last year of data (2011) was used to evaluate the performance of the model.

3.1 Data series analysis

To correctly develop the forecast model, some initial procedures had to be utilized. The first was to analyze the given time series, removing any possible inconsistent data and missing values. This step was performed through a computational routine, coded in Python language (Python 2.7).

After what, the wind speed data were adjusted to the hub height of the wind turbines, as the anemometer is installed 75 meters above the ground, while the hub of the turbines is located 44 meters above the ground. Assuming that the wind behavior follows a logarithmic profile, the following relation was used (Barthelmie et al., 1993):

$$\frac{U(z)}{U(h)} = \frac{ln\left(\frac{z}{z_0}\right)}{ln\left(\frac{h}{z_0}\right)} \quad (1)$$

where U(z) represents the wind speed measured by the anemometer (m/s), U(h) represents the wind speed at the desired height (m/s), z is the height of the anemometer (in meters), h is the hub height of the wind turbine (m) and z_0 represents the surface roughness (in meters), estimated as 0.03 meters (Lima et al., 2013).

Finally, the adjusted wind speed data with ten-minute granularity was averaged to hourly intervals, and the behavior of the data points was assessed through a quantitative analysis. Statistical parameters such as the mean, standard deviation, variance, skewness, and kurtosis were assessed and will be discussed later on in this paper.

3.2 ARMA/ARIMA models theory

The ARMA/ARIMA methodology was developed by Box & Jenkins in the 70s (Box et al., 2015). One of the objectives of this methodology is to forecast future events of a certain phenomenon, by using the past time series of this event (da Silva, 2005, Box et al., 2015).

ARMA models join autoregressive models (AR) and moving average models (MA) together. They can be represented by equation (2) below:

$$\tilde{z}_t = \varnothing_1 \tilde{z}_{t-1}\text{-}1 + \varnothing_p \tilde{z}_{t-p} + \alpha_t - \Theta_1 \alpha_{t-1} \dots - \Theta_q \alpha_{t-q} \tag{2}$$

where $\tilde{z}$ represents an autoregressive and moving average process; $\varnothing_p$ represents the autoregressive parameters; $\tilde{z}_{t-1}$ represents the past values of the time series; Θ_q represents the moving average parameters and α_{t-1} represents the random error (white noise process) (Box et al., 2015).

Equation 2 represents the combination of the models mentioned above. The autoregressive model models a process through the linear combination of the p past values of the time series ($\tilde{z}_t$) plus a random white noise term (a_t) (Box et al., 2015). The p values also inform the order of the AR model.

Moving average models are similar to the autoregressive models because they are also dependent on past values (q) of the time series used to generate the model, although the model combines (and weights) the q values with the white noise process (a_t). The q values inform the order of an MA model, just like the p values inform the order of the AR model (Box et al., 2015).

In both cases, it is assumed that the models represent processes with mean zero and variance σ^2 (Commandeur et al., 2007).

The ARMA approach has an important characteristic: it was developed to model a stationary time series, which can be problematic since many real-world phenomena do not exhibit a stationary behavior.

To overcome this limitation, it is possible to differentiate the time series with respect to a certain time interval, which aims to find a homogenous behavior of the time series between the selected range of time. Once this homogeneity is found, the series needs to be integrated back to the original time-step, allowing an ARMA model to be adjusted. This integration step is part of the name of this approach: Autoregressive *Integrated* Moving Average (ARIMA) models (Box et al., 2015), represented by equation (3) below:

$$w_t = \varnothing_1 w_{t-1} + \ldots + \varnothing_p w_{t-p} + a_t - \Theta_1 a_{t-1} - \ldots - \Theta_q a_{t-q} \quad (3)$$

where $\varnothing_i$ represents a stationary autoregressive operator and w_t can be understood as the differentiated time series. The definition of w_t is as follows:

$$wt = \nabla^d z_t \quad (4)$$

in this case, d represents the number of differences needed to achieve the stationary state (Box et al., 2015).

3.3 Stationarity of the Time series

The stationarity of a time series can be evaluated graphically by the autocorrelation function (ACF) and/or by testing the existence of unitary roots in the characteristic polynomial equation of the time series (Box et al., 2015). In this work, the stationarity of the wind speed time series was tested using both approaches. The ACF plot was compared to the Augmented Dickey-Fuller (ADF) unit roots test. The aim of the test for a general AR model given by $\Phi(B)z_t = a_t$ is to test the existence of a unit root in a general AR model, using the equation shown below (Box et al., 2015, Yang & Zhang, 2008):

$$\Delta z_t = \propto . z_{t-1} . \sum_{i=1}^{p} \varphi_i . X_{t-i} + a_t \quad (5)$$

The ADF test is a hypothesis test, where the null hypothesis, H_0 corresponds to the existence of a unit root in the equation (5) and is equivalent to the following statement:

$$\propto = \sum_{i=1}^{p+1} \varphi_i = 1 \quad (6)$$

The existence of a unit root in the AR operator $\Phi(B)$ can be interpreted as a strong indicator of the non-stationary nature of the time series (Box et al., 2015, Yang & Zhang, 2008).

3.4 Choice of the best model

Choosing a proper model requires the correct estimate of the number of AR and MA operators (p,q), as well as the number of differences (d) needed for reaching the stationarity condition of the time series. This choice is not always obvious and can be improved by statistical tests such as the *Akaike Information Criteria* (AIC) and the *Bayesian Information Criteria* (BIC), both employed on this work. The tests are based on the maximum likelihood of the values and the number of parameters of the models (Box et al., 2015, Emiliano, 2009).

The AIC test can be defined as follows:

$$AIC = \frac{2ln(\theta) + 2r}{n} \tag{7}$$

where ϴ represents the value of the maximum likelihood; r is the number of parameters, and n is the size of the sample (Box et al., 2015).

The BIC test can be represented by equation 8 below:

$$BIC = \ln(\hat{\sigma}_a^2) + r\frac{ln(n)}{n} \tag{8}$$

where $\hat{\sigma}_a^2$ represents an estimate of the maximum likelihood value; r and n are defined in the same way as in the AIC (Box et al., 2015).

In both cases, the best model will always be the one that shows smaller AIC or BIC values. The tests compare various possible ARMA/ARIMA models and indicate which of the selected models may be the best fit for the selected sample (time series) (Emiliano, 2009).

It is necessary to state that the tests are intended to support a decision and should not be the only decision criterion for the choice of the ARIMA model parameters.

3.5 Forecast Evaluation

Three statistical tests were used to evaluate the results generated by the ARMA/ARIMA models:

- Mean Absolute Error (MAE)

The MAE is a measure of the absolute difference between a forecast and the actual corresponding observation. The test is defined as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}(|for(i) - obs(i)|) \tag{9}$$

where for(i) represents the forecasted values, obs(i) represents the observed values and n represents the sample size used in the test. The utilization of the MAE test is supported by (Erdem et al., 2011).

- Root Mean Squared Error (RMSE)

The RMSE is a widely employed estimate of the performance of a model, mainly when the noise of the model tends to follow the normal distribution but is still valid for this work (Chai & Draxler, 2014, Gomes & Mine, 1998).

The RMSE is defined as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(|for(i) - obs(i)|)^2} \quad (10)$$

The parameters n, for(i) and obs(i) are defined identically as in the case of MAE.

- Nash-Sutcliffe Index (NS)

The Nash-Sutcliffe index is a measure of the efficiency of the model. The results of the index vary from -∞ to 1; the latter being the goal for a perfect model. NS values close to 0 indicates that the performance of the simulations is close to the mean of the data employed to build the model. Negative NS values indicate that the mean of the data is a better predictor than the model. The test is defined as follows (McCuen et al., 2006):

$$NS = 1 - \frac{\sum_{i=1}^{n}(|for(i) - obs(i)|)^2}{\sum(obs(i) - \overline{for(i)})^2} \quad (11)$$

where $\overline{for(i)}$ means the average of the forecasted values.

3.6 Wind power Forecast

The wind speed forecast is the fundamental result of the predictive model. From this result, the wind power forecast was performed for the Palmas Wind Farm. It was done by adjusting the forecasted wind speed values to the characteristic power curve of the wind turbine.

The power curve shows the behavior of the turbine according to different wind speeds. In this case, the wind turbine is an Enercon E40 and the power curve of the turbine is shown in figure Figure 1 below:

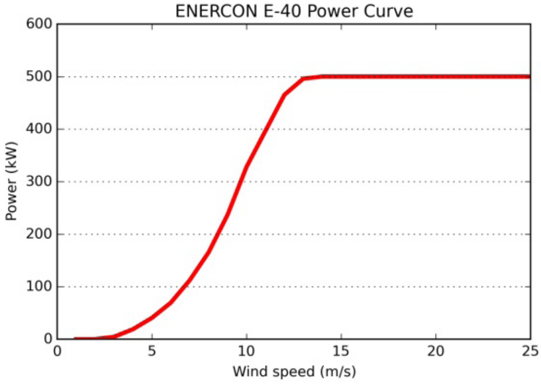

Figure 1 - Enercon E40 wind turbine power curve

Finally, the adjusted values are multiplied by the number of turbines of the wind farm (five in this case).

4 I RESULTS AND DISCUSSION

This section presents the results of the model for two randomly chosen dates, one in the winter of 2011 and another in the summer of the same year. The results consist of 100 forecasted values for the selected dates.

4.1 The behavior of the wind

The wind speed data is represented by the histogram shown in Figure 2, which classifies the occurrence frequency of observed wind speeds. The statistical distribution shows that most of the observed wind speeds occur within 4 m/s and 10 m/s, and the average wind speed is around 6 m/s for the period.

A Weibull distribution was fitted to the wind speed data distribution frequency, which revealed to be a good fit. The distribution has a shape factor of 2.67 and a scale factor of 7.17. These factors are used in the Weibull distribution, which represents the probability of occurrence of some wind speed at a certain time interval. This probability was calculated using the equation below.

$$w(v) = \left(\frac{a}{b}\right)\left(\frac{v}{b}\right)^{(a-1)} e^{-\left(\frac{v}{b}\right)^{a}} \quad (12)$$

where a is the shape parameter and b is the scale factor for any value in the range $0 < v < \infty$ (Patel, 1999).

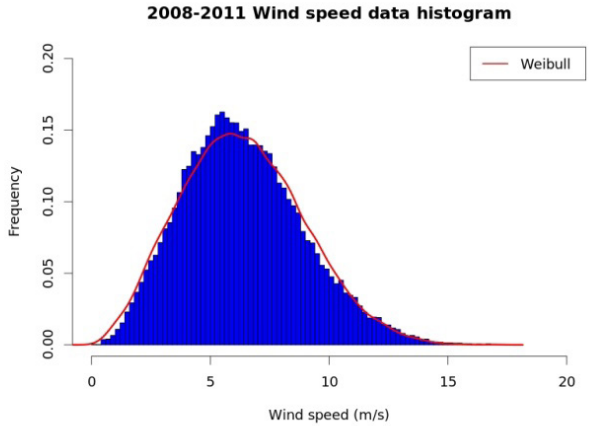

Figure 2 - Wind speed data distribution histogram

Quantitative assessment of the behavior of the time series was also performed. This considered statistics such as maximum, minimum and average wind speed throughout the period, as well as the standard deviation, skewness, and the kurtosis of the distribution of the data.

Table 2 shows the statistics for the wind speed time series. The positive skewness value indicates that most of the data is grouped below the average wind speed of 6.37 m/s. The kurtosis value indicates a sharper peak in data distribution (relative to the normal distribution). Both cases match with the data shown in the histogram.

Max. wind speed (m/s)	17.78
Average wind speed (m/s)	6.37
Min. wind speed (m/s)	0.23
Standard deviation	2.56
Skewness	0.44
Kurtosis	0.07

Table 2 - 2008-2011 hourly wind speed data series statistics

4.2 Stationarity

Following the methodology presented in the previous section, the stationary behavior of the time series was assessed visually and quantitatively. The autocorrelation function (ACF) was calculated and plotted, as shown in Figure 3. The confidence interval for the plot is 0.9 or 90%.

It can be observed from Figure 3 that the ACF function does not present a constant decay with time, as expected for a white noise process (Box et al., 2015), conversely, between the lag 10 and 15 the function begins to increase, a first indication that the time series has a non-stationary behavior.

The quantitative assessment of stationarity was done using the ADF test. Table 3 shows the results of the test.

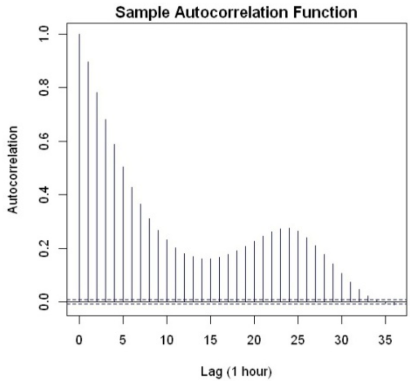

Figure 3 - Results of ACF

	Test statistics	Critical value
Original	-5.53	-2.58
1st Difference	-41.62	-2.58

Table 3 - ADF tests results

The results of the ADF test show that the original wind speed time series may have no unit root lying in the unit circle. However, the first difference of the time series exhibited more distant test statistics from the critical value. This fact and the conclusions taken from the ACF function suggested the development of an ARIMA model based on a differentiated time series instead of working with the original one.

4.3 Choice of the model parameters

The last step before the development of the WPF model was to decide the parameters of the model. As discussed in the previous section, to help in the decision process, the AIC and BIC tests were performed between a set of 20 possible ARIMA () models. The three best models are shown in Table 4 below:

Model	σ^2	AIC	BIC
ARIMA (1,1,2)	1,269	80596,10	80628,8
ARIMA (2,1,1)	1,269	80606,59	80639,28
ARIMA (3,1,2)	1,268	80592,39	80641,44

Table 4 - AIC & BIC tests results

The results of the AIC and BIC tests agree with the ACF plot and with the ADF test, showing that differentiation is necessary in order to obtain the best results. Thus, an ARIMA (1,1,2) was adjusted to forecast wind speed and its results are shown in the section below.

4.4 Forecasting model

The WPF model developed in this work is essentially a wind speed forecasting model designed to perform an extra step, which is to calculate the wind power from the corresponding wind speed forecasted value and wind turbine power curve. Thus we first developed the ARIMA (1,1,2) to forecast the wind speed, and only after that, the wind power was estimated.

The ARIMA (1,1,2) model followed the equation 13 below. As expected, this equation presents one autoregressive component and two moving average components. This characteristic is fixed for the model. The statistical software was able to recalculate and to update the coefficients (the numbers) of the equation within every new forecast.

$$w_t = 0.8609w_{t-1} - 0.8549a_{t-1} - 0.1427a_{t-2} \tag{13}$$

The model was able to forecast the wind speed up to three hours ahead. This was done by adjusting the time steps (lags) of the model. The model could be extended to as many steps as desired, but after three lags (or three hours ahead) the model lost its accuracy.

To check its strength against the seasonal variability, the model was set to forecast the wind speed of a random date of the summer (summertime forecast) and another random date of the winter (wintertime forecast). Figure 4 shows the forecasted results compared to actual wind speed data.

As can be seen in Figure 4, the one hour ahead forecasts performed during summertime and wintertime showed equally promising results. The results tend to degrade with the increase of the step of time, as can be seen for the two and three hours ahead forecasts, where the distance between the forecasted values and the observed wind speed values (the blue line) increase. This result was expected for an autoregressive model.

presents the results of the assessment of the performance of the models for the hourly wind speed forecast, where the results can be considered satisfactory, at least for forecasts up to three hours ahead. It also can be assessed from the results that the model is robust and is not greatly affected by seasonal variations.

Summertime Period			
	MAE(m/s)	**RMSE (m/s)**	**NS**
Lag = 1	0.71	0.92	0.78
Lag = 2	0.85	1.09	0.69
Lag = 3	0.99	1.28	0.57
Wintertime Period			
	MAE(m/s)	**RMSE (m/s)**	**NS**
Lag = 1	0.81	1.07	0.79
Lag = 2	1.01	1.35	0.67
Lag = 3	1.19	1.54	0.56

Table 5 - Wind speed forecasts evaluation results

4.5 Wind power forecast

The final step of the presented WPF model employs the wind turbine power curve to estimate the amount of wind power that could be generated from the corresponding forecasted wind speed.

The WPF results are shown in Figure 5 , where it can be noted that the model is not capable of forecasting extreme values accurately. The degrading of the forecasts with the increase of the time steps can also be noted.

Despite these difficulties, it is worth noting that the general behavior of the forecasts tends to follow the actual wind power time series, even for higher forecast horizons. Small differences between the energy generated by the wind farm and the forecasted energy show that the model can forecast wind power with a satisfactory level of precision, as shown in Table 6 below.

	Measured	Forecast (lag 1)	Forecast (lag 2)	Forecast (lag 3)
Energy (kWh)	115290.86	114474.22	112618.56	105524.43
Error (kWh)	–	816.64	2672.30	9766.43
Error (%)	–	0.7%	2.31%	8.47%

Table 6 - Differences of the wind power generated and forecasted

It can be inferred from the table above that the error between the observed and forecasted energy is small (0.7%) for the one hour ahead (lag = 1) wind power forecast. The error increases with the increase in the forecast horizon. For the two hours ahead forecast, the error percentage is 2.31%, while for the three hours ahead this number reaches 8.47%, which can still be considered acceptable for forecasting purposes.

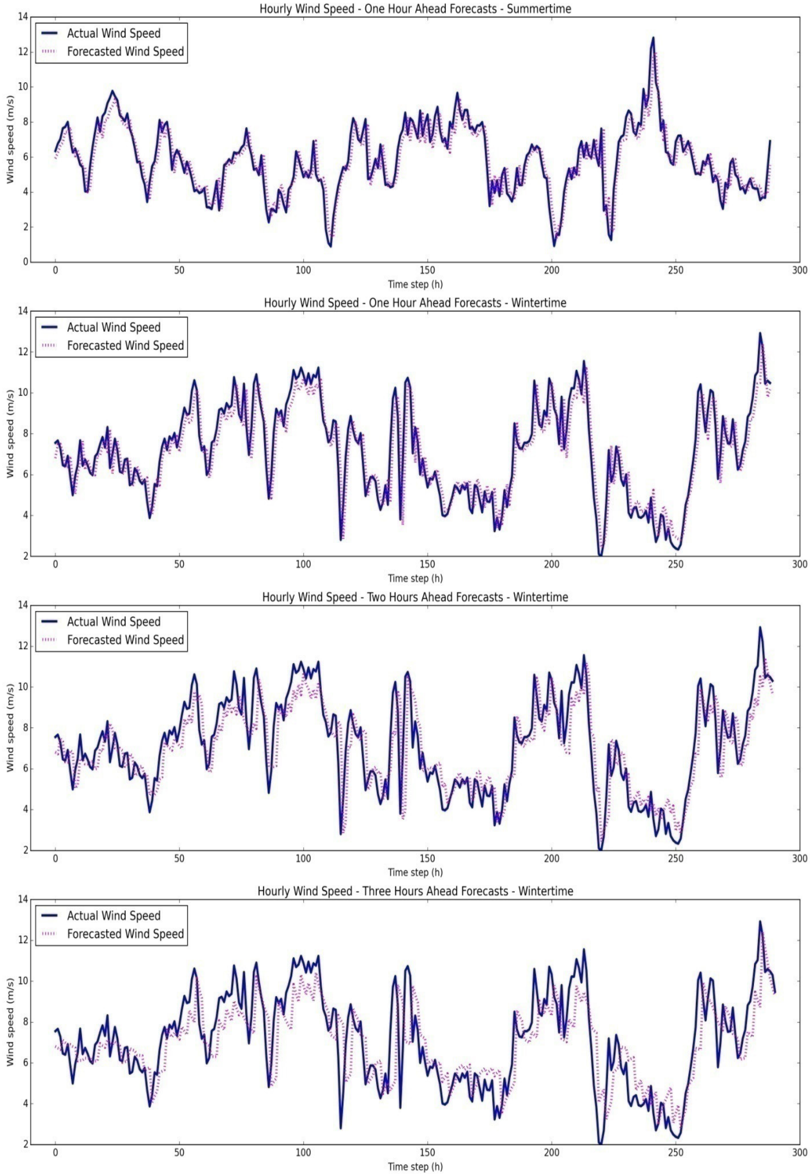

Figure 4 – Forecasting results according to different time steps and seasons of the year of 2011.

5 I CONCLUSIONS

The goals of this work were to show the development of a wind power forecasting (WPF) model and assess its performance. The model was designed to be a baseline model to be used by the wind power research group of the Department of Hydraulics and Sanitation (DHS) at the Federal University of Paraná.

The first goal, the development of the WPF model, was successfully achieved. The model has shown its ability to forecast the wind speed and the wind power for the Palmas Wind Farm up to three hours ahead in time.

The model presented degrading results with the increase of the horizon of the forecast. But the results still exhibited acceptable MAE, RMSE and NS results. The degrading phenomenon is also expected for an autoregressive model.

The wind power forecasting model also showed reasonably enough forecasts, and the computed maximum difference between the forecasted energy and the measured energy was only 8.47% for the three hours ahead forecasts.

In summary, the main goal of the work was accomplished and now it is expected that this model will serve its secondary purpose in the Department of Hydraulics and Sanitation (DHS) at the Federal University of Paraná.

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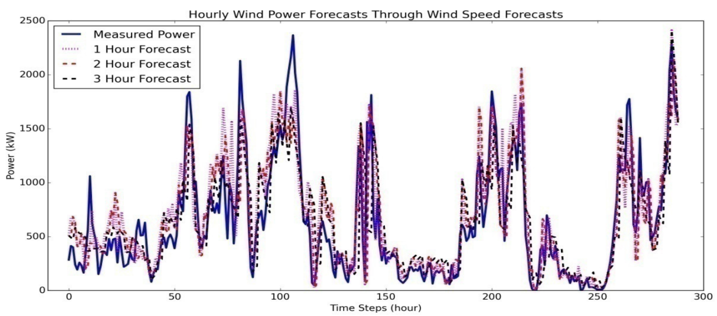

Figure 5 - Wind power forecasts performed through wind speed forecasts

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ÍNDICE REMISSIVO

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Resultados das Pesquisas e Inovações na Área das Engenharias 3

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