View metadata, citation and similar papers at core.ac.uk
brought to you by CORE
provided by Elsevier - Publisher Connector

Available online at www.sciencedirect.com
ScienceDirect
Energy Procedia 62 (2014) 676 – 685
Energy Procedia

6th International Conference on Sustainability in Energy and Buildings, SEB-14

Simplified method to derive the Kalman Filter covariance matrices to predict wind speeds from a NWP model

Conor Lynch[a,*], Michael J. OMahony[a], Ted Scully[b]

[a]Process, Energy and Transport Engineering Department, Cork Institute of Technology, Bishopstown, Cork, Ireland
[b]Computing Department, Cork Institute of Technology, Bishopstown, Cork, Ireland

Abstract

This paper espouses a simplified approach to predict wind speed 1 hour ahead for a wind turbine located on the Cork Institute of Technology (CIT) college campus by utilising a Kalman Filter to predict the bias between a campus based turbine and the output from a Numerical Weather Prediction (NWP) model for Cork Airport.

Furthermore, this paper investigates the optimum number of samples required (n) in a fixed sampling interval process to derive the covariance matrix of the system equation Q_t and the covariance matrix of the observation equation R_t. The main contents of this paper include wind speed analysis, state space analysis and Kalman Filtering application to Numerical Weather Prediction (NWP) data for wind speed prediction.

© 2014 The Authors. Published by Elsevier Ltd. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/3.0/).
Selection and peer-review under responsibility of KES International

Keywords: Kalman Filter; Wind Speed Prediction; Wind Power Prediction; NWP Models

1. Introduction

The limitations of the global resources of fossil and nuclear fuel have necessitated an urgent search for alternative sources of energy [22]. A wide body of literature states that micro-grids (μG) comprising of distributed generation (DG) of electricity, e.g. wind turbines, have a good chance of pervading the electricity infrastructure in the future [1,14,15]. The continued increase in the levels of greenhouse gas (GHG) has acted in recent years as a stimulus, prompting a reform of the legislation pertaining to primary energy production and its use. The significance of primary energy on GHG emissions is affirmed by the fact that 65% of GHG emissions in the World are currently due to the use and production of energy [20]. In March 2007, the European Union (EU) leaders commit to the climate and energy package, a set of binding legislation, which outlines ambitious targets for 2020. Collectively coined the 20-20-20 targets, they set three primary objectives [9];

* Corresponding author. Tel.: +353-21-433-5066
E-mail address: conor.lynch@mycit.ie

1876-6102 © 2014 The Authors. Published by Elsevier Ltd. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/3.0/).
Selection and peer-review under responsibility of KES International
doi:10.1016/j.egypro.2014.12.431

- 20% reduction in EU greenhouse gas emissions from 1990 levels.
- Increase EU energy consumption from renewable sources to 20%.
- 20% improvement in the EU's energy efficiency.

In an effort to meet these stringent targets, together with the intentions of the 2030 and 2050 road maps [8], many countries are increasing their installed capacity of renewable wind generation [3]. It can be observed from equation (1), that the power output P_{wind} (in watts) of a wind turbine depends on the wind speed u and any error in the wind speed forecast would yield a large (cubic) error in wind power. Subsequently the accurate short-medium term prediction of wind speed has become a very intensive area of research [26].

$$P_{wind} = 1/2 * \rho * A * u^3 * C_p \tag{1}$$

where:

ρ = Density of air (kg/m3)
C_p = Wind turbine coefficient of performance - specified by the manufacturer
A = Rotor swept area
u = Wind speed

It is well known that Numerical Weather Prediction (NWP) models usually exhibit systematic errors in the forecast of certain meteorological parameters, such as wind speed, especially near ground level. This drawback is a result not only of the shortcoming in the physical specification, but also of the inability of these models to successfully handle sub-grid phenomena [19]. Horizontal grid-dimensions for mesoscale meteorological NWP models generally have sides between 5 km (3 miles) and several hundred kilometers in length. In order to reduce these drawbacks, one of the most successful approaches to extract results that better reflect local conditions is the adoption of the Kalman Filtering technique [3,5,6,19]. An alternative option to down scale NWP models include methods derived from Model Output Statistics (MOS). Cheng [7], in his analysis of the strengths and weaknesses of MOS, Running-Mean Bias Removal and the Kalman Filter (KF) techniques for improving model forecasts states that the KF is superior to MOS for wintertime cold pools and quiescent warm season patterns. Furthermore, MOS requires a long training dataset and therefore can be difficult to apply to sites that lack a long and complete historical record.

This objective of this paper is twofold: First to present an overview of the Kalman Filter and to detail a simplified methodology to derive the covariance matrix of the system equation Q_t and the covariance matrix of the observation equation R_t of a Kalman Filter. Nilsson [23] states that R_t might be estimated by making measurements and calculating the variance, but estimating Q_t is more difficult, since the state vector X_t cannot be measured directly. Also Q_t acts as a waste basket for unknown modelling errors. From the current state of the art, it can be found that many methods for estimating Q_t and R_t from the output sequence $Z_{t+1/t}$, see equation (3), are suggested. In contrast to the simplified method outlined in this paper, Mehra et al [21] and Odelson [24] discuss different methods of adaptive filtering, each with alternative methods to obtain Q_t and R_t. They include: bayesian, maximum likelihood (ML), correlation, and covariance matching methods. Secondly, from a case study, to detail the application of the Kalman Filter to an NWP model to predict the wind speed for CIT through predicting the bias that exists between the output of the NWP and the observed wind speeds at CIT. As previously stated, these wind speeds can then be used as an input to predict the potential wind power generation.

This paper is organised such that Section 2 details the NWP model used. This is followed by an overview of the Kalman Filter methodology in Section 3. An intuitive illustration on the application of the Kalman Filter to a NWP model is configured in Section 4 as well a simplified methodology to ascertain an estimate of the covariance matrices Q_t (the system equation) and R_t (the observation equation). This is in contrast to more cumbersome methods such as employing a support vector regression (SVR) based state-space model or fitting a Gauss-Markov curve to the power spectral density (PSD) to estimate Kalman Filter variables. The findings and results are displayed in Section 5. Finally, in Section 6 the discussion and conclusions drawn are presented.

2. The Modelling System

This paper uses wind speed data from the YR.NO NWP model [27]. The YR.NO, a joint service by the Norwegian Meteorological Institute and the Norwegian Broadcasting Corporation, have developed a weather NWP model that collates data and content from of a number of bodies. The main NWP models include the HIRLAM (HIgh Resolution Limited Area Model) model and the AROME (Application of Research to Operations at Mesoscale) modelling system shown in red and green respectively in Fig. 1.

Officially launched since September 2007, YR.NO is unique in Europe because of the very detailed (hour-by-hour) weather forecasts and its free data policy [27]. It offers weather forecasts in English (in addition to Norwegian Nynorsk and Norwegian Bokml) for nearly 1 million locations in Norway and 9 million worldwide, one of which being Cork Airport in Ireland. The open source weather forecast data includes 12 hour ahead hour-by-hour wind speed data in ms^{-1} in graphical or XML format (see Fig. 2 - 4). This is in contrast to other short range NWP models such as that used by Met Èireann, which only provides wind speed data in the form of colour coordinated velocity contours in knots (nautical miles per hour). However, more detailed hour-by-hour wind speed data is offered by Met Èireann but on a proprietary basis.

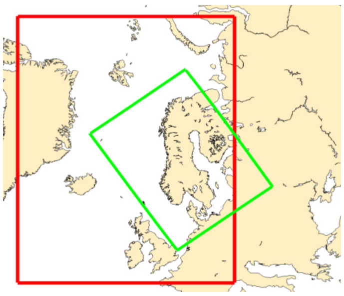


Fig. 1: Map of area covered in the YR.NO NWP model [27]

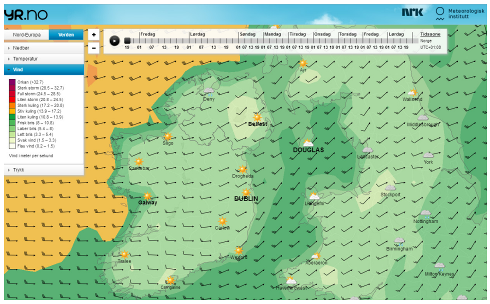
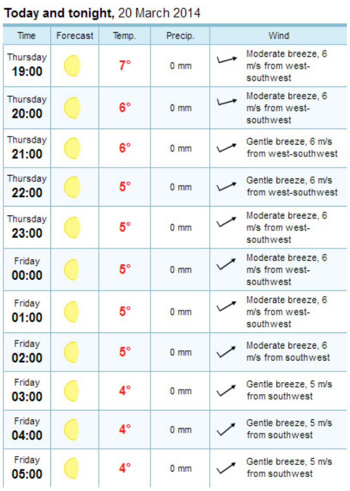


Fig. 2: Graphical overview of YR.NO Wind Map for Ireland [27]



Today and tonight, 20 March 2014

Time	Forecast	Temp.	Precip.	Wind
Thursday 19:00		7°	0 mm	Moderate breeze, 6 m/s from west-southwest
Thursday 20:00		6°	0 mm	Moderate breeze, 6 m/s from west-southwest
Thursday 21:00		6°	0 mm	Gentle breeze, 6 m/s from west-southwest
Thursday 22:00		5°	0 mm	Gentle breeze, 6 m/s from west-southwest
Thursday 23:00		5°	0 mm	Moderate breeze, 6 m/s from west-southwest
Friday 00:00		5°	0 mm	Moderate breeze, 6 m/s from west-southwest
Friday 01:00		5°	0 mm	Moderate breeze, 6 m/s from west-southwest
Friday 02:00		5°	0 mm	Moderate breeze, 6 m/s from southwest
Friday 03:00		4°	0 mm	Gentle breeze, 5 m/s from southwest
Friday 04:00		4°	0 mm	Gentle breeze, 5 m/s from southwest
Friday 05:00		4°	0 mm	Gentle breeze, 5 m/s from southwest

Fig. 3: Graphical 12hr ahead wind forecast [27]

```
<forecast>
- <tabular>
  - <time to="2014-05-11T19:00:00" from="2014-05-11T18:00:00">
      <!-- Valid from 2014-05-11T18:00:00 to 2014-05-11T19:00:00 -->
    <symbol var="01d" name="Clear sky" numberEx="1" number="1"/>
    <precipitation maxvalue="0.1" minvalue="0" value="0"/>
      <!-- Valid at 2014-05-11T18:00:00 -->
    <windDirection name="West-northwest" code="WNW" deg="287.6"/>
    <windSpeed name="Fresh breeze" mps="8.1"/>
    <temperature value="14" unit="celsius"/>
    <pressure value="1007.9" unit="hPa"/>
  </time>
  - <time to="2014-05-11T20:00:00" from="2014-05-11T19:00:00">
      <!-- Valid from 2014-05-11T19:00:00 to 2014-05-11T20:00:00 -->
    <symbol var="01d" name="Clear sky" numberEx="1" number="1"/>
    <precipitation maxvalue="0.1" minvalue="0" value="0"/>
      <!-- Valid at 2014-05-11T19:00:00 -->
    <windDirection name="West-northwest" code="WNW" deg="285.3"/>
    <windSpeed name="Moderate breeze" mps="6.3"/>
    <temperature value="13" unit="celsius"/>
    <pressure value="1008.2" unit="hPa"/>
  </time>
  - <time to="2014-05-11T21:00:00" from="2014-05-11T20:00:00">
      <!-- Valid from 2014-05-11T20:00:00 to 2014-05-11T21:00:00 -->
    <symbol var="04" name="Cloudy" numberEx="4" number="4"/>
    <precipitation maxvalue="0.2" minvalue="0" value="0.1"/>
      <!-- Valid at 2014-05-11T20:00:00 -->
    <windDirection name="West-northwest" code="WNW" deg="282.6"/>
    <windSpeed name="Gentle breeze" mps="5.3"/>
    <temperature value="13" unit="celsius"/>
    <pressure value="1008.6" unit="hPa"/>
```

Fig. 4: XML 12hr ahead wind forecast [27]

The direct output from the NWP model at time step t, (which represents the wind speed at Cork Airport for the purpose of this paper) is then processed by the Kalman Filter in an effort to remove the bias that exists between this output and that of our desired location, the campus of the Cork Institute of Technology (CIT) in this case study - this is outlined further in Section 3.

3. The Kalman filter methodology

To make this paper an independent entity it includes a cursory interpretation of the steps within the Kalman Filter algorithm as outlined by [11,12,16,18,25]. Kim [18] describes the Kalman Filter, first published in 1960 by R.E.Kalman [16], as a sequential (recursive) execution of four steps. The equation subscripts used, detailed by Burns ([4], pg. 286-288) adopt an intuitive approach detailing the time step and the information available at that time step. For example, the subscript term $(t + 1/t)$ means data used at time $t + 1$ based on information available at time t. The Kalman Filter is applied to get a grasp of an unknown state vector X_t, over a range of time steps t. The system model is described by the equation:

$$X_{t+1/t} = A_{t/t}.X_{t/t} + w_t \tag{2}$$

and the correlation between the measured vector and the unknown state vector is inferred by the equation:

$$Z_{t+1/t} = C_{t/t}.X_{t+1/t} + v_t \tag{3}$$

where:

A_t, C_t = Matrices in the state space equation
$X_{t/t}$,$X_{t+1/t}$ = State of the system
$Z_{t+1/t}$ = Predicted output from the Kalman Filter
w_t = system noise
v_t = measurement noise

A_t, C_t, as well as w_t and v_{t+1},the vectors of the disturbance noise and measurement noise covariance matrices Q_t and R_t respectively, have to be determined prior to the implementation of the Kalman Filter. A more in depth explanation of these terms, their derivation and any assumptions made are outlined in section 4. The following is an overview of the steps involved in the recursive Kalman Filter algorithm:

3.1. Step One - Predict state and error covariance

To begin the recursive Kalman Filter algorithm, an initial value of $X_{t/t}$ (the state vector) and $P_{t/t}$ (the covariance in Kalman Filtering) must be assumed. A good initial guess can lead faster to a more accurate prediction. These initial values are then substituted into equations (4) and (5) below.

$$X_{t+1/t} = A_{t/t}.X_{t/t} \tag{4}$$

$$P_{t+1/t} = A_{t/t}.P_{t/t}.A^T_{t/t} + Q_t \tag{5}$$

where:

Q_t = disturbance noise covariance matrix. A simplified approach to estimate this variable is detailed in section 4

3.2. Step Two - Compute Kalman Gain

The value of the Kalman gain K_{t+1} converges as $t \to \infty$. The Kalman Gain, from equation (6) acts as a weighting of the relative importance of the residual with respect to the previous estimate. This is explained further in step three.

$$K_{t+1/t} = P_{t+1/t}.C^T_{t/t}(C_{t/t}.P_{t+1/t}.C^T_{t/t} + R_t)^{-1} \tag{6}$$

where:

R_t = measurement noise covariance matrix. A simplified approach to estimate this variable is detailed in section 4

3.3. Step Three - Compute the Estimate

The difference, $(Z_{t+1} - C_{t/t}.X_{t+1/t})$ calculated within equation (7), is called the residual. The residual reflects the discrepancy between the predicted or estimated measurement $C_{t/t}.X_{t+1/t}$ and the actual measurement Z_{t+1}. A residual of zero means that the two are in complete agreement [10]. The Kalman Gain acts as a weighting of the relative importance of the residual with respect to the previous estimate.

$$X_{t+1/t+1} = X_{t+1/t} + K_{t+1}(Z_{t+1} - C_{t/t}.X_{t+1/t}) \tag{7}$$

3.4. Step Four - Compute the error covariance

Here, by employing equation (8), the covariance in Kalman Filtering is updated for the next time step t and the sequence begins again in a recursive manner.

$$P_{t+1/t+1} = (I - K_{t+1/t}.C_{t/t})P_{t+1/t} \tag{8}$$

where: I = identity matrix

According to the Kalman Filters characteristics, the recursive algorithm can lead to more accurate results by applying more cycles using equations (4) through (8) above.

4. Applying a Kalman Filter to a NWP model case study

The YR.NO NWP model, outlined in section 2, was used to provide 1 hour ahead wind speed predictions for Cork Airport in Ireland. The wind speed predictions for the foreseeable 12 hours were updated every 12 hours at 04:00 and 16:00 by retrieving a YR.NO XML file. Then, in a similar manner to the work implemented by Galanis [11,12] and Louka [19], the Kalman Filter technique, outlined in section 3, was applied to predict the state vector X_t, representing the coefficients of a third-order polynomial function, equation (9), used to define the bias of the wind speed between Cork Airport and the 10kW Bergey wind turbine located on CIT college campus in Ireland - see Fig.5 below.

$$Z_t = x_{0,t} + x_{1,t}.m_t + x_{2,t}.m_t^2 + x_{3,t}.m_t^3 + v_t \tag{9}$$

The coefficients x_t are parameters that have to be estimated initially from historical wind speed data and m_t is the direct output of the NWP model which represents Cork Airport in this case. Thus we get the following for the state vector and observation matrices:

$$X_t = [x_{0,t}\ x_{1,t}\ x_{2,t}\ x_{3,t}]^T \tag{10}$$

$$C_t = [1\ m_t\ m_t^2\ m_t^3] \tag{11}$$

As a result, the system and observation equations, equations (2) and (3) respectively, correspondingly become:

$$X_{t+1/t} = A_t.X_t + w_t \tag{12}$$

$$Z_{t+1} = C_t.X_t + v_t \tag{13}$$

From equation (10) it can be observed that X_t is a (4x1) matrix. Aditionally w_t (derived from X_t - X_{t-1}) is a (4x1) matrix. Thus A_t, the system matrix, in order to follow matrix convention is required to be (4x4) identity matrix. Here a (4x4) identity matrix is used for A_t.

$$A_t = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{14}$$

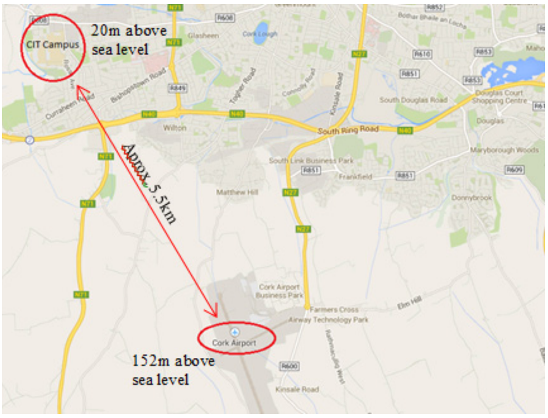


Fig. 5: Map showing yr.no NWP model node Cork Airport, and the desried location CIT Campus [13]

The Kalman Filter covariance matrix P_t is initially considered to be diagonal, indicating limited correlations between different coordinates of the state vector X_t. The diagonal elements are initially assigned a large value to indicate a low credibility of our first guess [17]. In this case we propose:

$$P_t = \begin{bmatrix} 4 & 0 & 0 & 0 \\ 0 & 4 & 0 & 0 \\ 0 & 0 & 4 & 0 \\ 0 & 0 & 0 & 4 \end{bmatrix} \tag{15}$$

4.1. Optimal sampling time to derive Qt and Rt

One of the aims of this paper is to present a simplified methodology to calculate an estimate of system covariance matrix Q_t and the measurement covariance matrix R_t.

Equations (16) and (17) below were employed by Galanis et al [12] and Louka et al [19] in an effort to calculate the (4x4) system covariance matrix Q_t and the (1x1) measurement covariance matrix R_t. It is worth noting that the estimates of Q_t and R_t were based on a sample of the last 7 values of X_t. Additionally the equations adopted appear to contradict matrix mathematical convention as outlined by K.A. Stroud [17] p.340 the input to equation 16 is a (4x1) matrix and equation 16 suggests that this is squared.

$$Q_t \equiv \frac{1}{6}\sum_{i=0}^{6}\left(\left((x_{t-i} - x_{t-i-1}) - \left(\frac{\sum_{i=0}^{6}(x_{t-i}-x_{t-i-1})}{7}\right)\right)\right)^2 \tag{16}$$

$$R_t \equiv \frac{1}{6}\sum_{i=0}^{6}\left(\left((y_{t-i} - H_{t-i}.x_{t-i}) - \left(\frac{\sum_{i=0}^{6}(y_{t-i}-H_{t-i}.x_{t-i})}{7}\right)\right)\right)^2 \tag{17}$$

This paper uses equations (18) and (19) that adopt a transparent and intuitive approach. These alternative equations adopt a step-by-step approach in line with fundamental mathematical matrix laws. A series of tests has led to the conclusion that the appropriate number of samples n required to calculate Q_t and R_t is 3 (a moving average of the previous 3 observed values of X_t). This paper uses the following equations to investigate the appropriate n to estimate Q_t and R_t

$$Q_t \equiv \frac{1}{n-1}\sum_{i=0}^{n-1}(w_i - \bar{w})(w_i - \bar{w})^T \tag{18}$$

where:

$$w_i = (X_{t-i} - X_{t-i-1}) \tag{18a}$$

$$\bar{w} = \left(\frac{\sum_{i=0}^{n-1} (X_{t-i} - X_{t-i-1})}{n} \right) \tag{18b}$$

$$R_t \equiv \frac{1}{n-1} \sum_{i=0}^{n-1} (v_i - \bar{v})(v_i - \bar{v})^T \tag{19}$$

where:

$$v_i = (\overbrace{Z_{t-i}}^{\text{Actual}} - \overbrace{C_{t-i}.X_{t-i}}^{\text{Predicted}}) \tag{19a}$$

$$\bar{v} = \left(\frac{\sum_{i=0}^{n-1} (Z_{t-i} - C_{t-i}.X_{t-i})}{n} \right) \tag{19b}$$

4.2. 4.2. Calculating the predictive and actual wind speed

Once Q_t and R_t have been calculated, the Kalman Filter is then called upon to estimate the predicted wind speed of the 10kW Bergey wind turbine for a 1 hour ahead time horizon. Forecasted wind speeds at hub height (40m height) of the turbine from the Kalman Filter were then compared to wind speed data recorded at 40m as well as scaled 40m wind speeds from wind speed data recorded at a 60m height. The recorded 60m wind speed data was downloaded from an NRG Syphonie data logger linked to the anemometer on CIT Campus. The actual 60m wind speeds were scaled using the Hellmann exponential law, equation (20), a simplified version of the Monin-Obukhov method [2].

$$\frac{v_2}{v_1} = \left(\frac{z_2}{z_1} \right)^{\alpha} \tag{20}$$

where:

v_1, v_2 are wind speeds at different heights (ms^{-1})
z_1, z_2 are different heights that wind speed is measured (m)
α is the Hellman exponent dependent upon location, terrain and the stability of the air. NOTE: By rearranging equation (20), site specific α values were calculated for each wind direction based on historical wind data.

5. Results

Fig.6 illustrates the validity in utilising the Kalman Filter as a tool to predict the wind speed 1 hour ahead for a desired height from a NWP model. As data recorded at hub height would be corrupted by the blade, ordinarily the wind speed for a desired hub height is scaled from actual wind speed data recorded above or below the height of interest. Here data is recorded at a 60m height (to scale from) and an assumed hub height of 40m in order to investigate the capacity for the Kalman Filter to predict wind speeds 1 hour ahead for a desired hub height of 40m through the post-processing of open source NWP data.

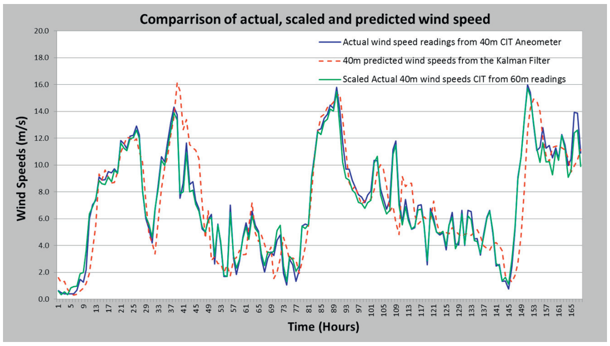


Fig. 6: Actual Recorded , Scaled and Predicted Wind Speed by Kalman Filter for 40m hub height

Table 1: Statistical analysis of Fig.6 Scaled 40m readings (green), predicted 40m readings by Kalman Filter (red)

RMSD	2.03	0.47
NRMSD	0.13	0.03
Absolute Percentage Error (APE)	31%	9%

Table 1 outlines a statistical analysis of the actual 60m wind speed scaled to 40m and the predicted wind speed by Kalman Filter for 40m in contrast to actual recorded wind speed data for a 40m height. These results for a 1 week period suggest an increase of 22% in the APE. This is expected since, unlike the scaled data, the Kalman Filter is predicting wind speeds / power output for 1 hour ahead.

$$RMSD = \sqrt{\frac{\sum_{i=1}^{n}(x_{1,t} - x_{2,t})^2}{n}} \tag{21}$$

$$RMSD = \frac{RMSD}{x_{max} - x_{min}} \tag{22}$$

where:

RMSD = Root Mean Square Deviation

NRMSD = Normalised Root Mean Square Deviation

$x_{1,t}$ = Actual Wind Speed

$x_{2,t}$ = Predicted Wind Speed

x_{max} = Max Wind Speed

x_{min} = Min Wind Speed

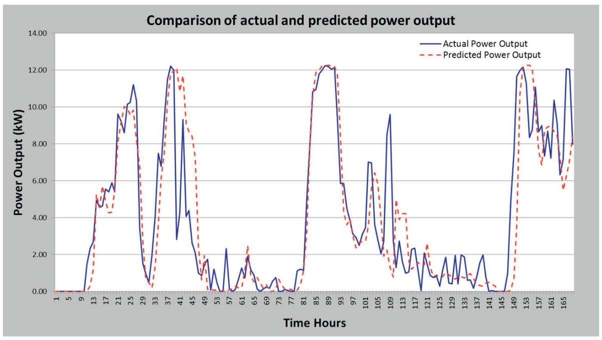


Fig. 7: Actual Power Output v Predicted Power Output by Kalman Filter for 40m hub height

A further investigation was conducted where n, which is depended on the frequency of the local wind patterns, was in-putted into equations (18) and (19) above. To investigate the appropriate number of samples required (n), values of *n* ranging from 2 to 8 were applied to equations (18) and (19) above. The resulting predicted wind speeds were then plotted against the actual recorded wind speed data at a 60m height for a 1 hour ahead time horizon over a 1 week period (168 hours) - see Fig. 8-11. From Tables 2-4 it can be observed that a value of $n = 3$ derives the lowest RMSD and NRMSD value, inferring an *n* value of 3 yields predictive wind speed values closest to that of the true wind speed value. Tables 3 and 4 also show that the Kalman Filter performs well at deriving wind speed predictions at hub height which in reality is difficult to achieve largely due to obstructions caused by the wind turbine itself.

Table 2: Statistical analysis of (*n*) for predictive v actual 60m wind speeds recorded @ 60m for 1 hour ahead time horizon

Samples required (*n*)	n=2	**n=3**	n=4	n=5	n=6	**n=7**	n=8
RMSD	2.795	**1.961**	2.173	2.171	2.148	**2.150**	2.132
NRMSD	0.165	**0.116**	0.128	0.128	0.127	**0.127**	0.126

Table 3: Statistical analysis of (*n*) for predictive v actual 40m wind speeds recorded @ 40m for 1 hour ahead time horizon

Samples required (*n*)	n=2	**n=3**	n=4	n=5	n=6	**n=7**	n=8
RMSD	2.224	**2.033**	2.152	2.157	2.138	**2.163**	2.197
NRMSD	0.143	**0.130**	0.138	0.138	0.137	**0.139**	0.141

Table 4: Statistical analysis of (*n*) for predictive v scaled **actual** 40m wind speeds recorded @ 40m for 1 hour ahead time horizon

Samples required (*n*)	n=2	**n=3**	n=4	n=5	n=6	**n=7**	n=8
RMSD	3.562	**1.911**	2.051	2.047	2.033	**2.049**	2.033
NRMSD	0.231	**0.124**	0.133	0.133	0.132	**0.133**	0.132

6. Discussion and Conclusions

This paper details a concise and curtailed approach to predict wind speeds for a 1 hour ahead time horizon though the post-processing of an existing NWP model using a Kalman Filter. However, before the Kalman Filter can be applied a number of terms must be determined, the most cumbersome of these being the system covariance matrix Q_t and the measurement covariance matrix R_t. The performance of the Kalman Filter is closely linked to the accuracy of these parameters thus it is necessary to be able to estimate these variables for a particular problem. This paper presents equations (18) and (19) and subsequently investigates the optimal number of samples *n* to apply in an effort to acquire an accurate estimate of these variables to optimise the Kalman Filter in order to minimise the error between the predicted and the true value. To verify geographical independence, possible future work would involve an investigation of the appropriate *n* value when the Kalman Filter outlined in this paper is applied to the NWP model for other geographical locations. Also an area of consideration for future work is the investigation of the wind speed frequency band width for a particular *n* value.

7. Acknowledgements

The author would like to thank all those who contributed to this paper especially the following: the Irish Research Council for Science, Engineering and Technology (IRCSET) and United Technologies Research Center Ireland (UTRCI) who co-funded this research, as well as the people of YR.NO, a Norwegian website for weather forecasting for use of the numerical weather prediction model.

References

[1] Nathan Ainsworth, Mitch Costley, James Jamal Thomas, Michael Jezierny, and Santiago Grijalva. Versatile Autonomous Smartgrid Testbed (VAST): A flexible, reconfigurable testbed for research on autonomous control for critical electricity grids. *2012 North American Power Symposium (NAPS)*, pages 1–5, September 2012.

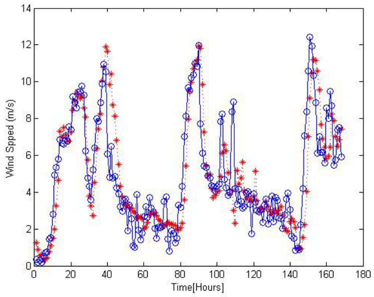


Fig. 8: Actual (blue) v predictive (red) wind speed for $n = 3$

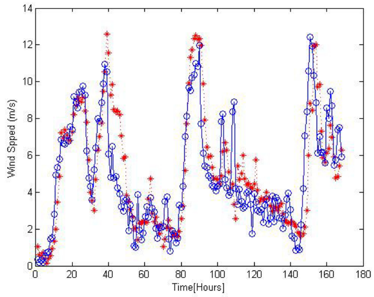


Fig. 9: Actual (blue) v predictive (red) wind speed for $n = 7$

[2] Francisco Bañuelos ruedas and César Ángeles Camacho. Methodologies Used in the Extrapolation of Wind Speed Data at Different Heights and Its Impact in the Wind Energy Resource Assessment in a Region. 2011.

[3] Hamed Babazadeh, Student Member, Wenzhong Gao, Senior Member, and Lin Cheng. An Hour Ahead Wind Speed Prediction by Kalman Filter. 2012.

[4] Roland Burns. *Advanced Control Engineering*. Butterworth-Heinemann, 2001.

[5] Federico Cassola and Massimiliano Burlando. Wind speed and wind energy forecast through Kalman filtering of Numerical Weather Prediction model output. *Applied Energy*, 99:154–166, November 2012.

[6] Kuilin Chen and Jie Yu. Short-term wind speed prediction using an unscented Kalman filter based state-space support vector regression approach. *Applied Energy*, 113:690–705, January 2014.

[7] William Y. Y. Cheng and W. James Steenburgh. Strengths and Weaknesses of MOS, Running-Mean Bias Removal, and Kalman Filter Techniques for Improving Model Forecasts over the Western United States. *Weather and Forecasting*, 22(6):1304–1318, December 2007.

[8] Commission EU. 2030 framework for climate and energy policies. (March 2012):1–5, 2013.

[9] EU Commission. Analysis of options to move beyond 20% greenhouse gas emission reductions and assessing the risk of carbon leakage. *Analysis of options to move beyond 20% greenhouse gas emission reductions and assessing the risk of carbon leakage*, 2010.

[10] The Discrete Kalman Filter. The Discrete Kalman Filter, 2014.

[11] G. Galanis, PC. Chu, and G. Kallos. Statistical post processes for the improvement of the results of numerical wave prediction models. A combination of Kolmogorov-Zurbenko and Kalman filters. 4(1):23–32, 2011.

[12] G. Galanis, P. Louka, P. Katsafados, I. Pytharoulis, and G. Kallos. Applications of Kalman filters based on non-linear functions to numerical weather predictions. *Annales Geophysicae*, 24(10):2451–2460, October 2006.

[13] Google. Google Maps, 2014.

[14] Santiago Grijalva, Mitch Costley, and Nathan Ainsworth. Prosumer-based control architecture for the future electricity grid. *2011 IEEE International Conference on Control Applications (CCA)*, pages 43–48, September 2011.

[15] Michiel Houwing, Rudy R Negenborn, Marija D Ilić, and Bart De Schutter. Model Predictive Control of Fuel Cell Micro Cogeneration Systems. pages 708–713, 2009.

[16] R E Kalman. A New Approach to Linear Filtering and Prediction Problems 1. 82(Series D):35–45, 1960.

[17] K.A.Stroud with Dexter J. Booth. *Essential Mathematics for Science and Technology*. 2009.

[18] Phil Kim. *Kalman Filter for Beginners with MATLAB Examples*. A-Jin Publishing Company, 2011.

[19] 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. *Journal of Wind Engineering and Industrial Aerodynamics*, 96(12):2348–2362, December 2008.

[20] Gustavo a. Marrero. Greenhouse gases emissions, growth and the energy mix in Europe. *Energy Economics*, 32(6):1356–1363, November 2010.

[21] R. Mehra. Approaches to adaptive filtering. *IEEE Transactions on Automatic Control*, 17(5):693–698, October 1972.

[22] E. M. Natsheh, a. Albarbar, and J. Yazdani. Modeling and control for smart grid integration of solar/wind energy conversion system. *2011 2nd IEEE PES International Conference and Exhibition on Innovative Smart Grid Technologies*, pages 1–8, December 2011.

[23] Martin Nilsson. Kalman Filtering with Unknown Noise Covariances. (6):1–4, 2006.

[24] Brian J. Odelson. Estimating Disturbance Covariances From Data For Improved Control Performance by. 2003.

[25] M Rastgoo, Z ; Azadi and S ; Hajjam. Post-Processing of the WRF Output for 10-meter Wind Speed and 2-meter Temperature Using Nonlinear Kalman Filtering Method. 110:3–6.

[26] Saurabh S Soman, Hamidreza Zareipour, Senior Member, Om Malik, and Life Fellow. A Review of Wind Power and Wind Speed Forecasting Methods With Different Time Horizons. 2010.

[27] Yr.no. Norwegian weather forecasting website, 2014.